APPLICATION OF AN OPTIMUM QUANTIZER ALGORITHM TO PCM AND ADPCM SPEECH CODERS

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APPLICATION OF AN OPTIMUM QUANTIZER ALGORITHM TO

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

SUMMARY

A study has been performed to determine the advantage of employing locally optimum quantization to waveform speech coders. An algorithm for rapidly calculating the quantizer characteristic that minimizes the mean-squared quantization error has been developed. The algorithm performance was studied to determine its convergence, rate of computation and accuracy characteristics for a wide range of parameter variations. Histograms of amplitude probability distributions measured from a segment of speech or of an analytically generated probability distribution are provided as input to the algorithm. Quantizers of 2 to 256 levels with uniform, Gaussian, Laplacian, gamma and speech-histogram distributed quantization levels were calculated for comparisons. Computer simulations of PCM and ADPCM speech coders were conducted using uniform, Laplacian, gamma and locally optimum quantizers. Comparisons of speech coder outputs were made based upon signal to quantization noise ratios (SNR) and listening tests. The comparative studies indicate that use of an optimum quantizer calculated from a single spoken sentence will give an average 1.4 dB SNR improvement over use of a gamma-distributed quantizer, and an average 9.2 dB SNR improvement over use of a uniform-distributed quantizer. The amount of measured and perceived improvement depends upon number of quantization levels, coder type, block length and speaker.

CHAPTER I

INTRODUCTION

In the design of information communication or storage systems in which a continuous signal is represented as a discrete signal, it is desirable to make the discrete representation as efficient as possible in order to conserve bandwidth in the channel, or memory in the storage system. Conversion of a continuous signal into a discrete representation is a two-part process involving sampling and quantization. Through sampling, a quantity representing the amplitude of the signal is periodically retained for further processing. Quantization is a nonlinear process in which the time sampled continuous signal amplitude is represented as elements from a finite set of discrete amplitudes. This process of quantization induces an error in the discrete signal representation that is equivalent to the difference between the discrete signal amplitude and the continuous signal amplitude for each sample of the quantizer input. The induced error is called quantization error. For efficient representation of the continuous signal it is desired to minimize some statistic of the quantization error. Many such statistics have been considered. Perhaps the most interesting and widely developed approach is the Max quantizer [1] which minimizes the statistical mean square quantization error (MSE).

This study shall quantify the improvement that use of the optimum quantizer realizes over the use of other quantizers in two types of speech coders. Through the use of computer simulations, the considerations required when implementing a speech coder employing an optimum quantizer were noted. Several different sentences from different speakers were statistically analyzed for mean, variance and amplitude histograms. Optimum quantizers were designed using these estimated statistics for each sentence. Each sentence was coded by PCM and ADPCM (Adaptive Differential Pulse Code Modulated) speech coders employing several different quantizers.

A rapid, stable algorithm for calculating the optimum quantizer was used in the simulations. The iterative method suggested by Max [1] and Bruce [2] requires numerical integration on each iteration and has been found to be neither fast nor stable. The Max and Bruce methods also consider quantizers based upon analytical probability density functions. In 1979 Esteban, Menez and Boeri [3] described a variation of the Max algorithm that requires a two step iterative process in which the integrals have been replaced by sums, and the probability density functions by a histogram. The Esteban algorithm exhibits the rapid, stable characteristics that are necessary to calculate the optimum quantizer in a block-adaptive speech coder.

Much effort has been expended in this study to establish the accuracy and convergence characteristics of the algorithm. Optimum quantizers derived from well known probability distributions have been published in papers by Max [1], Paez and Glisson [4], and Esteban et al. [3]. After some minor changes to the Esteban algorithm for the purposes of this study, several optimum quantizers were calculated using uniform, Laplacian, Gaussian and gamma distributed histograms. The resulting quantizer characteristics and quantizer MSE were compared with the published results. Since a straightforward method of mathematically proving that the algorithm converges to the minimum mean squared error solution has not been determined, the idea of convergence is supported by experimental evidence. It is important to be confident that the algorithm gives accurate, stable solutions for analytical probability distributions which closely model speech since when actual speech is the source of the histogram used in the quantizer algorithm, there is little with which to compare the resultant quantizer characteristic. We will assume, and attempt to show that the speech histogram derived quantizer exhibits a lower MSE than any other quantizer of equal number of quantization levels.

PCM and ADPCM speech coders were chosen as the quantizer applications vehicle since they represent examples of simple and complex (respectively) waveform speech coders, and encompass the range of applications that may be considered. Comparisons to determine the improvement of the quantizer optimized for a particular speech histogram over other quantizers are based primarily upon coder output signal to quantization noise ratio (SNR). Quantizer MSE is also used for comparison since it is inversely proportional to SNR. Limited subjective testing was employed to determine if the objective measures correlate with any audible improvement in the coder output speech. Quantizers with uniform, Laplacian, and gamma distributed characteristics constitute the set with which the optimum quantizers are compared. Investigation of PCM coder operation using an optimum quantizer provides an initial indication of quantization improvement when used in other types of coders. In applications such as the ADPCM coder, the quantizer is designed using the coder difference signal statistics. This suggests that the Laplacian and gamma distribution models do not apply and an optimum quantizer should give better results.

The use of an optimum quantizer on a block of speech implies that a new quantizer characteristic is periodically calculated. The quantization levels are then transmitted (or stored) with the coded speech. It is important that the optimum quantizer calculation be quite rapid for locally optimum quantization to be performed in real time. A study of the algorithm has been included to determine rules for choosing algorithm parameters that will yield acceptable minimization of the MSE in the least amount of time. Information concerning number and type of calculations required for a desired quantizer is given. From this, the minimum block length may be computed for any given processor.

A theoretical development of the optimum quantizer algorithm is presented in Chapter II. The program OPT1, implementing an optimum quantizer calculation algorithm is discussed in Chapter III. This discussion also includes a description of the speech files that are used in the coder simulations. Chapter IV contains the algorithm accuracy, convergence and parameter study tests and results. In Chapter IV we will show how well OPT1 performs in computing an optimum quantizer. The PCM and ADPCM speech coder simulations are discussed in Chapter V with the listening test results. A list of the symbols and mnemonics used in this thesis is given in Appendix A.

CHAPTER II

OPTIMUM QUANTIZER ALGORITHM DEVELOPMENT

General Definitions

A quantizer is a device that performs the function of mapping each amplitude sample at its input onto a finite set of N numbers. N represents the number of quantization or reconstruction levels. In the following discussion we assume the amplitude of the quantizer input signal is sampled every T seconds. T is chosen to be a period, given by the sampling theorem such that no aliasing occurs. The sampled signal, x(n) is a sequence of elements of the infinite set of numbers between x_{min} and x_{max}. Thus, x(n) is represented with infinite precision and zero error. Figure 1 illustrates a general quantizer characteristic in which a number, y(n) chosen from a finite set of N numbers $(y_1, y_2, \ldots, y_{N-1}, y_N)$ on the quantizer output, is assigned to each input value, x(n) such that $x_{min} < x(n) \leq x_{max}$. In this discussion, $x_{min} = x_0$ and $x_{max} = x_N$. For example, if the input is x(n) such that $x_{N-2} < x(n) \leq x_{N-1}$ then the quantizer output, y(n) will be assigned the value y_{N-1}. The quantization error, e(n) is defined as

$$e(n) = y(n) - x(n) . \tag{1}$$

Figure 2 is a block diagram representing the relationships between the time continuous signal x(t), the discrete quantizer output, y(n) and the

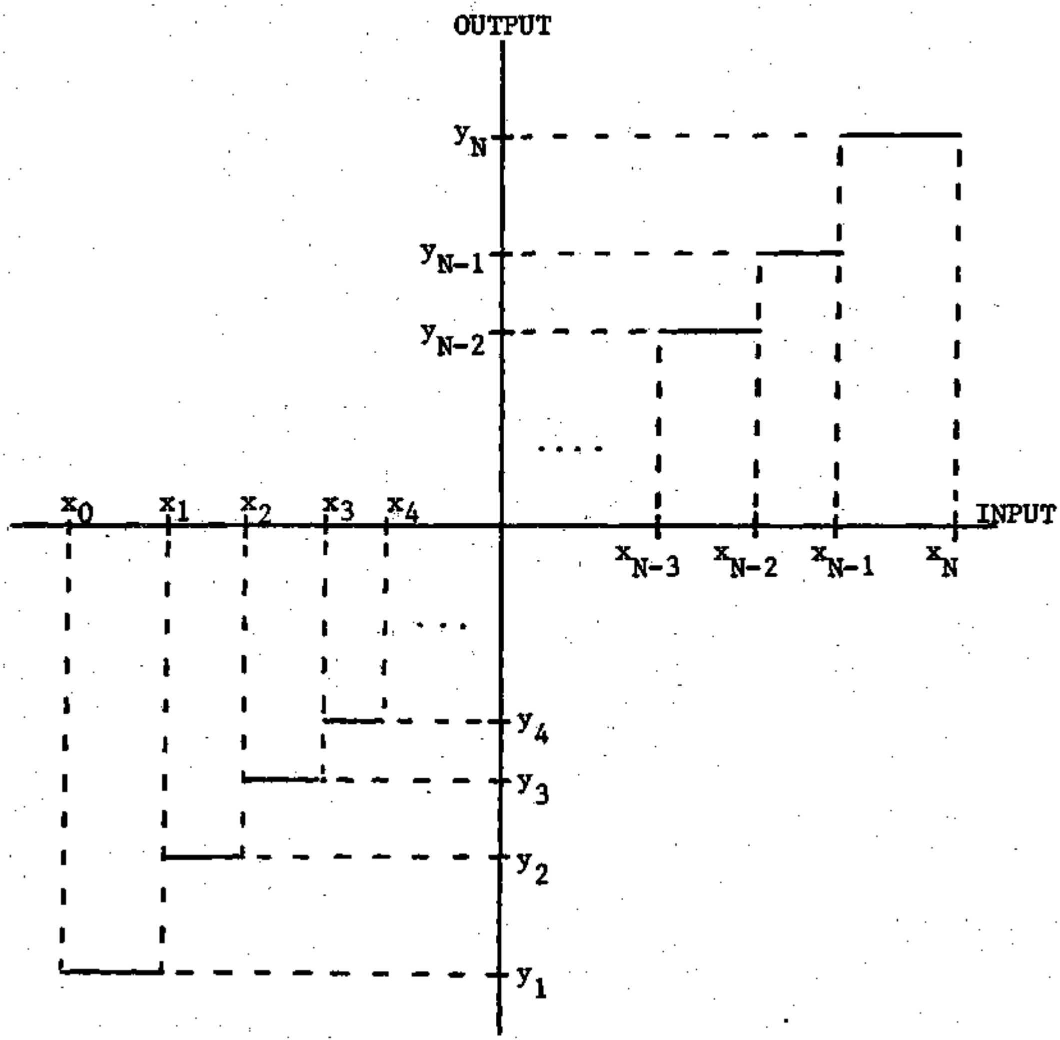


Figure 1. General Quantizer Characteristic

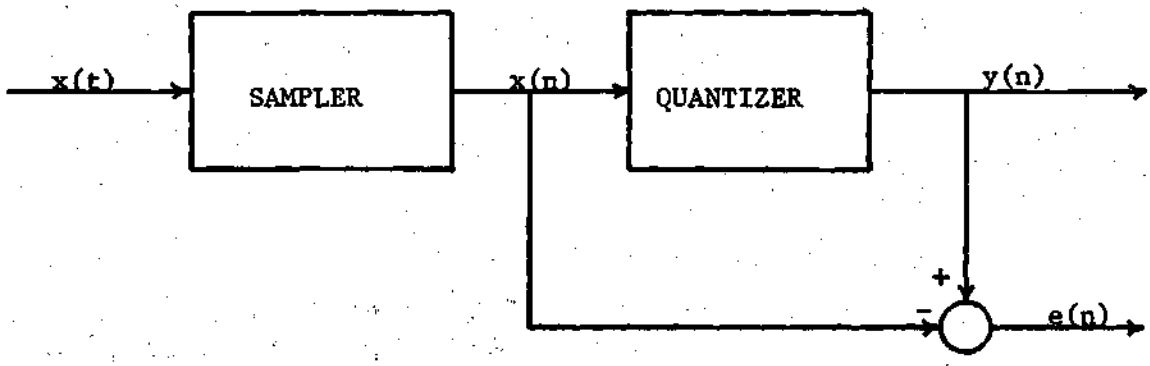


Figure 2. Quantizer Signal Block Diagram

quantization error, e(n). The quantizer can be viewed as a memoryless device since the output only depends upon the current input sample. The quantizer is also a nonlinear device since it does not support superposition. To develop an optimum quantizer we wish to minimize some function of the quantization error, e(n).

Max Algorithm

Max [1], in his treatment of the optimum quantizer attempts to minimize the quantizer induced distortion, D which is defined as the expected value of some function, g of the quantization error, ie.

$$D = E\{g(e(n))\} \quad . \tag{2}$$

Minimization of equation (2) results in a set of expressions describing the general optimum quantizer. Bruce [2] describes a general class of quantizers in which the function g(x) can be any non-negative function of its argument. In the current study we will only consider a special case in which $g(x) = x^2$, thus the distortion is now

$$D = E\{(e(n))^2\} = E\{(y(n) - x(n))^2\} \quad . \tag{3}$$

Since there are only N discrete values possible for y(n) the distortion can be rewritten as

$$D = \sum_{k=1}^{N} E\{(y_k(n) - x(n))^2\} \tag{4}$$

where $y_k(n)$ is the quantizer output at the k^{th} of N levels. Thus, the distortion is the sum of the contribution to the total from each of N separate quantization levels. This discretization of the distortion calculation allows us to perform the minimization on each quantization level. Following Max's [1] calculations, expansion of the expected value for a quantizer input signal with a probability density function p(x) yields

$$D = \sum_{k=1}^{N} \int_{x_{k-1}}^{x_k} (y_k - x)^2 \, p(x) \, dx \, . \tag{5}$$

To minimize the distortion, the first partial derivatives of D are taken and set equal to zero. Expressions for x_k and y_k are found as

$$\frac{\partial D}{\partial x_k} = \frac{\partial D}{\partial y_k} = 0$$

$$\frac{\partial D}{\partial y_k} = 0 = 2y_k \int_{x_{k-1}}^{x_k} p(x) \, dx - 2 \int_{x_{k-1}}^{x_k} x \, p(x) \, dx \, .$$

Solving for y_k gives

$$y_k = \frac{\int_{x_{k-1}}^{x_k} x \, p(x) \, dx}{\int_{x_{k-1}}^{x_k} p(x) \, dx} \qquad \text{for } k = 1,2,\ldots,N. \tag{6}$$

Similarly, for x_k

$$\frac{\partial D}{\partial x_k} = 0 = (y_k^2 - 2y_k x_k + x_k^2)\, p(x_k) - (y_{k+1}^2 - 2y_{k+1}x_k + x_k^2)\, p(x_k)\ .$$

Solving for x_k gives

$$x_k = (y_k + y_{k+1})/2 \qquad \text{for } k = 1,2,\ldots,N-1. \tag{7}$$

To find the optimum quantizer characteristic we have 2N-1 equations to be solved for 2N-1 variables, the set of N reconstruction levels (y_1, $y_2,\ldots y_N$) and the set of N-1 decision levels (x_1, $x_2,\ldots,x_{N-1}$). The remaining two decision levels are endpoints of the input signal range and are given as

$$x_0 = x_{min}$$

$$x_N = x_{max}\ .$$

From the set of equations described by (7), one can see that each decision level is located halfway between each two consecutive reconstruction levels. Also, note that each reconstruction level is located at the centroid of the portion of the probability density curve between each set of two successive decision levels. To solve these equations, Max suggests an iterative process as follows:

1) Specify the input amplitude range endpoints x_0, x_N.
2) Choose x_1. This must be an educated guess.
3) Solve (6) for y_1. This may require numerical integration.
4) Solve (7) for y_2.

5) Solve (6) for x_k, $k = 2,3,4,\ldots,N$. This requires iteratively solving (6) for y_k assuming a value for x_k, until the equality is met.

6) Repeat 4) for y_{k+1}.

7) Repeat 5) for x_k, $k=k+1$.

8) Repeat 6) and 7) until x_N is calculated.

Steps 2) through 7) represent one iteration of the algorithm. The computed x_N is then compared with the x_N specified in step 1). If $x_{N,\text{computed}} \neq x_{N,\text{specified}}$ another iteration is required with a new choice of x_1.

Max suggested that solution of equation (6) could easily require numerical integration if p(x) is not a simple function. An iterative routine that requires at least 2N numerical integrations on each iteration is a very time consuming process. A dynamic programming technique is suggested by Bruce [2] to obtain a minimum MSE solution with a minimum number of iterations. Barnwell [5], in a simulation similar to the Max algorithm noted that the error surface was not simple and exhibited several local minima for small variations in the x_1 start level choice. Given these observations one can see that the solution is neither stable nor rapid, and does not appear appropriate in a periodically updated speech coder application.

Discrete Algorithm

Esteban [3] suggests a modification of the Max algorithm by making two important changes. First the input signal probability density is given not as a function, p(x) but rather as a histogram p_j.

This change is sensible with respect to the present application since it is desired to design the optimum quantizer using the statistics of a specific utterance. The use of an analytical probability density function, p(x) approximates the statistics of an ensemble of speech utterances and is therefore less exact. By expressing p(x) at only discrete points (as a histogram) the integrals in equation (6) can be rewritten as

$$y_k = \frac{\sum_{j=i_{k-1}}^{i_k} x_j' \, p_j}{\sum_{j=i_{k-1}}^{i_k} p_j} \qquad \text{for} \quad k = 1,2,\ldots,N \tag{8}$$

where
$$i_k = \frac{Nk}{M} + 1 \tag{8a}$$

and
$$x_j' = \frac{x_{max} - x_{min}}{N} \cdot (j - 1) + x_{min} \tag{8b}$$

where M is the number of bins in the amplitude histogram. The i_k is constrained to be an integer for use as limits in the summation. Now the solution of 2N-1 equations for the optimum quantizer characteristic requires no integration in the centroid calculations. The second change Esteban suggests is to perform the calculations as a two step iterative process. The process follows:

1) Choose an initial set of N+1 decision levels, x_k.

2) Solve for N reconstruction levels, y_k using (8).

3) Solve for N-1 decision levels, $(x_1, x_2, \ldots, x_{N-1})$, using (7).

4) Repeat 2) and 3) until the desired precision is obtained.

Esteban states that this algorithm will converge upon the minimum MSE quantizer solution with each iteration. Due to the relative simplicity of the calculations, this algorithm is well suited to rapid calculation of the optimum quantizer and does not exhibit the instability problems associated with the Max method.

Simulations Algorithm

For the simulations in this study, an optimum quantizer algorithm similar to the Esteban approach (equations (7) and (8)) was used. The refinements are in the specification of the initial sequence of decision levels, and in the calculation of the reconstruction levels at each iteration. To reduce the number of iterations required, the initial set of decision levels, or start sequence is carefully chosen to be close to the optimum result. A maximum entropy starting calculation is used in which the decision levels are chosen such that they divide the amplitude histogram into regions of equal area. The area of any one histogram region is determined by

$$A = \frac{1}{N} \sum_{j=1}^{M} p_j = \sum_{j=i_{k-1}}^{i_k} p_j \qquad (9)$$

where N is the number of levels in the quantizer (or regions of equal area) and M represents the number of count bins in the histogram. To determine the start sequence $(x_1, x_2, \ldots, x_{N-1})$ equation (9) must be solved for i_k, an integer representation of the k^{th} decision level, thus the largest i_k is found such that

$$A - \sum_{j=i_{k-1}}^{i_k - 1} p_j \leq p \qquad \text{for } k = 1,2,\ldots,N-1. \tag{10}$$

is true. The i_k can then be linearly related to the x_k by

$$x_k = \frac{(x_{max} - x_{min})}{N}(i_k - 1) + x_{min} \quad . \tag{11}$$

The second refinement of the Esteban algorithm concerns the calculation of the reconstruction levels when the decision levels are not exactly located on histogram boundaries. In this situation, linear interpolation is used across histogram bins to obtain a more accurate result and to increase the rate of convergence that would otherwise be lost due to integer truncation. Figure 3 provides an illustration of this calculation in which the centroid y_k is found by

$$y_k = \frac{\sum_{j=a_2}^{a_8} x_j' \, p_j - \frac{1}{2\Delta}(x_{k-1}^2 - a_2^2)\, p_{a_2} + \frac{1}{2\Delta}(x_{k-1}^2 - a_8^2)\, p_{a_8}}{\sum_{j=a_2}^{a_8} p_j - \frac{1}{\Delta}(x_{k-1}^2 - a_2^2)\, p_{a_2} + \frac{1}{\Delta}(x_{k-1}^2 - a_8^2)\, p_{a_8}} \tag{12}$$

where $\Delta = a_7 - a_6 = a_6 - a_5 = a_5 - a_4 \ldots$ The histogram bin width, and the a_n are arbitrary distances along the histogram amplitude axis.

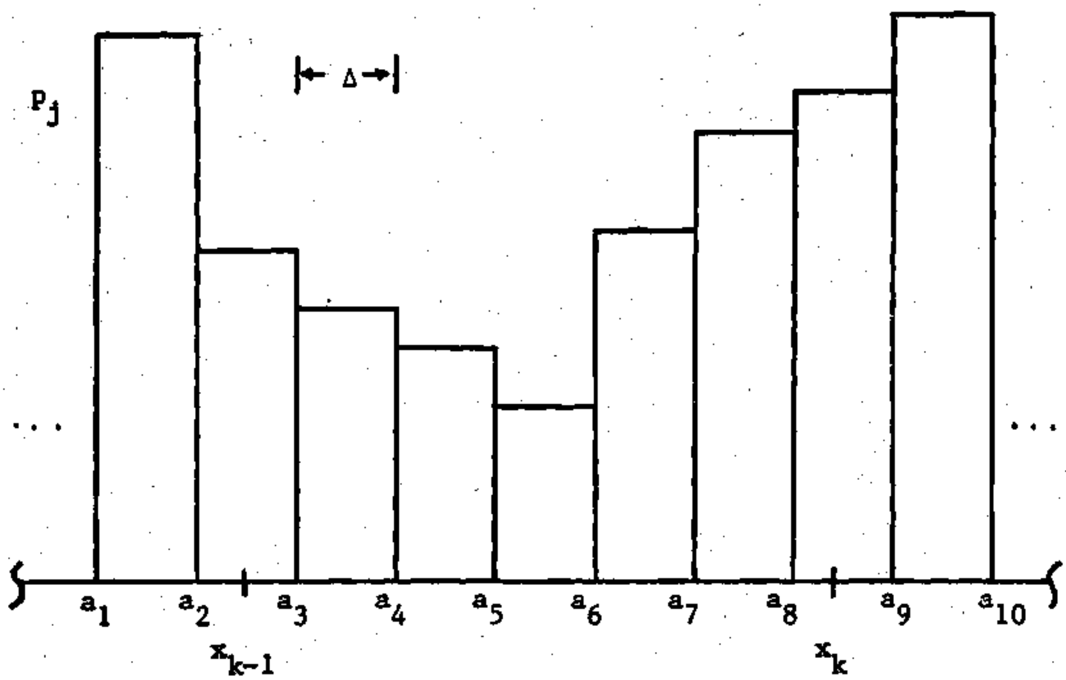


Figure 3. Centroid Calculation with Interpolation

The algorithm is terminated as Esteban suggests when the decision levels of the b^{th} iteration differ by less than a specified amount from the decision levels of the $b-1^{th}$ iteration. If C is defined as the convergence limit, the algorithm terminates when

$$|x_k^{(b)} - x_k^{(b-1)}| \leq C \qquad \text{for each} \quad k = 1,2,\ldots,N. \tag{13}$$

An optimum quantizer, if properly designed, must have a smaller mean squared quantization error than any other quantizer of equal number of levels. This assumes that the quantizer input is the same signal whose statistics were used to design the optimum quantizer. Comparisons based upon MSE of various quantizers are of interest. In the present study, MSE is calculated as

$$\mathrm{MSE} = \sum_{k=1}^{N} \sum_{j=x'_{k-1}}^{x'_k} (y_k - x_j)\, p_j^2 \, . \tag{14}$$

Equation (14) will be used as a basis of comparison of quantizers of different types.

To develop an expression for the quantized signal to noise ratio (SNR), we first note that the variance of the quantization error, σ_e^2 can be expressed as

$$\sigma_e^2 = E\{e^2(n)\} = E\{(y(n) - x(n))^2\} \, . \tag{15}$$

Equation (15) is exactly the same as (3), used in the development of the optimum quantizer, hence the distortion is $D = \sigma_e^2$. Input SNR can then be written as

$$\mathrm{SNR} = \frac{\sigma_x^2}{\sigma_e^2} = \frac{\sum^{L} x^2(n)}{\sum^{L} e^2(n)} \tag{16}$$

where σ_x^2 is the variance of the input, and L is the number of input samples. It may now be seen that the quantizer MSE and SNR are inversely proportional as given by the expression

$$\mathrm{MSE} = \frac{1}{\mathrm{SNR}} \ \sigma_x^2 \quad . \tag{17}$$

Hence, comparisons based upon MSE also indicate trends in SNR. This point is important when comparisons of the algorithm results are made with published results since SNR comparisons cannot be directly made.

CHAPTER III

SPEECH CODER SIMULATIONS

General Procedure Description

Five sets of computer simulations were used to investigate the performance of the optimum quantizer algorithm and the effects of optimum quantization in waveform speech coders. The simulations include a 1) Accuracy test, 2) Convergence test, 3) OPT1 Parameter Study, 4) PCM coder simulation and 5) ADPCM coder simulation. The first three simulations require a two part process; 1) measure sentence statistics, 2) calculate quantization levels and quantizer MSE. In the Accuracy test, we show that the optimum quantizer algorithm, OPT1 (a computer program) accurately computes the minimum mean squared error quantizer characteristic for histograms of known distributions. The accuracy of the results is determined through comparison with other published optimum quantizer results. In Chapter II a maximum entropy start sequence was described for beginning the algorithm. The Convergence test was performed to gain two items of information. First, we showed that the maximum entropy start sequence was an acceptable starting point for the algorithm, with other start sequences resulting in the algorithm converging upon the minimum mean squared error result more slowly. Second, an indication of rate of convergence is shown to aid in the selection of certain program parameters. Finally, the Parameter Study was performed to provide rules in specifying OPT1 input parameters that allow for the accurate calculation of quantizer characteristics in a minimum amount of time. The final two coder simulations require an additional step consisting of coding the speech file. The coder simulations used the program parameters that were determined from the Accuracy, Convergence and Parameter test simulations. For PCM and ADPCM speech coders, actual speech files were statistically measured, optimum quantizers computed, coding performed and performance measures recorded. This body of performance data constitutes the applications study section of this thesis. All simulations and tests are implemented on a Data General Eclipse computer system using FORTRAN programming. The program SPCHSTAT is used to calculate the required statistics of the speech files. OPT1 and several related subroutines calculate the optimum quantizer and perform the PCM coder simulation. Program ADPCOD developed by Barnwell [5] is used to perform the ADPCM coder simulation once OPT1 has provided it with quantizer characteristics. Program listings for ADPCOD, OPT1 and related subroutines are provided in Appendix F.

In this study of locally optimum quantization, a single block type was chosen for all the simulations. Initial estimates indicated that a quantizer characteristic could be calculated in one to ten seconds. Figure 4 presents a set of curves indicating the percentage of time that would be dedicated to the speech portion of a transmission as a function of the block length, assuming a new quantizer characteristic is transmitted with each block. For this graph, it is assumed that the speech is sampled at an 8 KHz rate and the quantization levels are themselves quantized to 12-bits uniform. It can be seen that for blocks

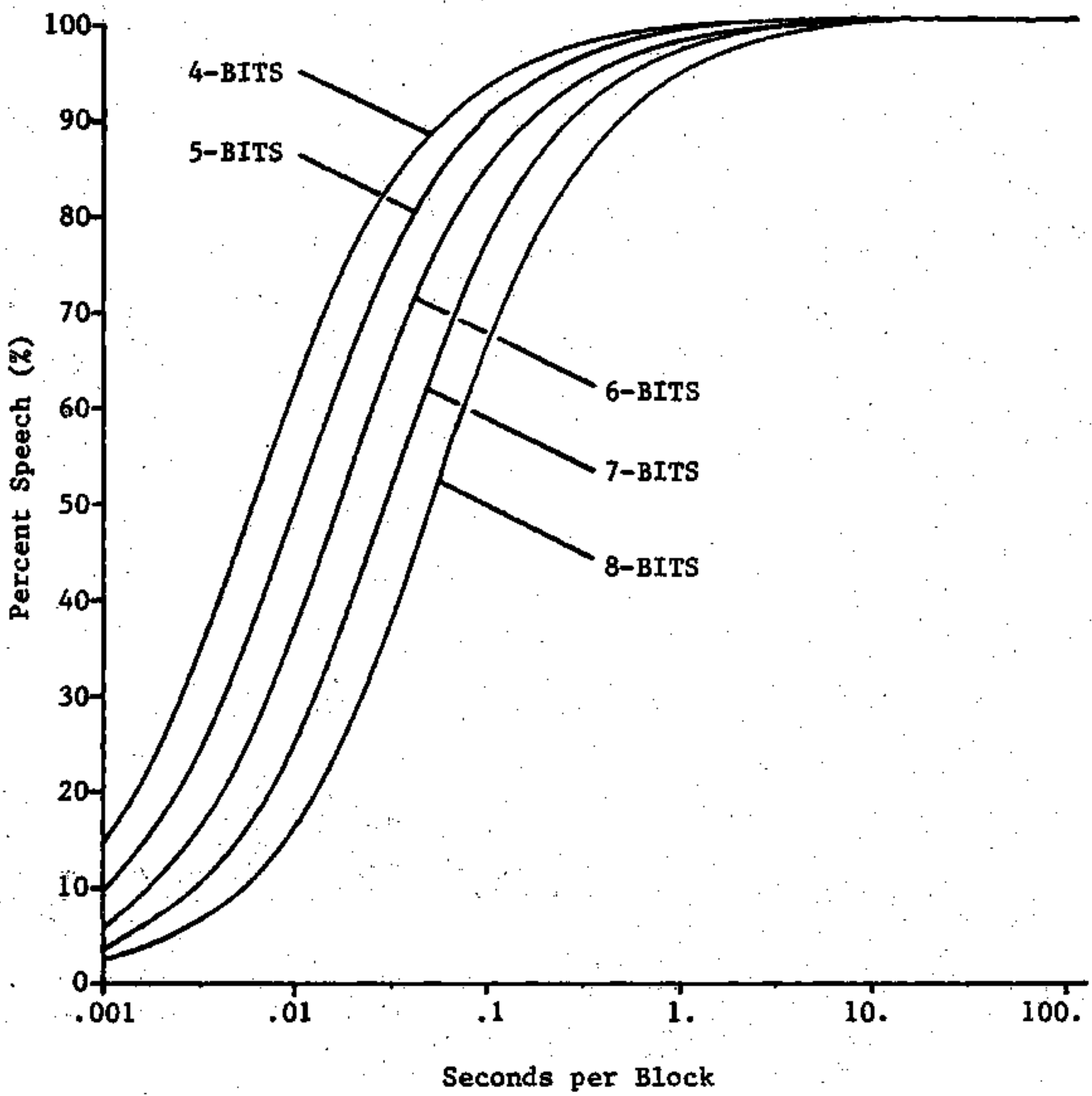


Figure 4. Percentage of Speech in a Locally Optimum Quantized Transmission

of length greater than one second the percentage of speech changes very little for any of the quantizers considered. A convenient block designation in the range of greater than one second is the sentence. Therefore, in this study it was decided to apply the optimum quantizer study to blocks that are separate sentences.

Description of Speech Files

Six sentences were used in the simulations to provide an ensemble of actual speech inputs. The sentences contain a wide variety of phonemes and are spoken by male and female speakers. Figure 5 illustrates the method used in representing each sentence in digital form within the computer. Each sentence is represented and stored as an integer file. Table 1 lists the specific sentences along with the speech file name that was used throughout the simulations. Each speech file contains 24576 samples, or 3.072 seconds of data. With speech blocks of this length, we may be able to calculate the optimum quantizer characteristic and apply it to the speech in real time. The Duration column of Table 1 gives the time in seconds that elapsed between the start of speech detection and the end of speech detection for each speech file. The endpoint detections were made visually from a graphical output of the file sample amplitudes. From the table we see that the speech files contain from 69 % to 85 % speech, including silence between words. For programming simplicity and consistency of the testing procedure, all 24576 samples of each speech file were coded with MSE and SNR measurements computed on the entire file. In all of the simulations, the input speech was assumed to be represented by an

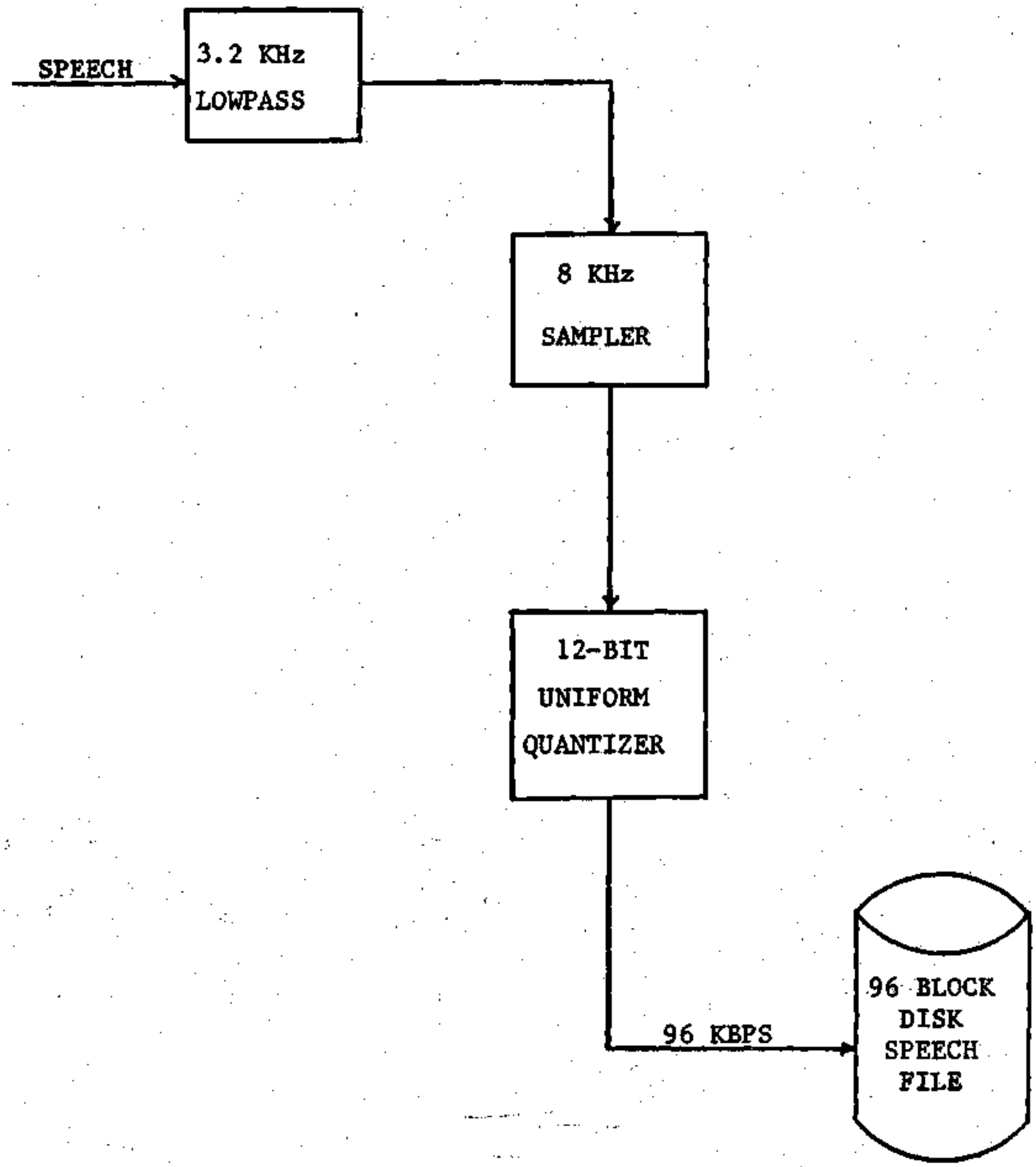


Figure 5. Speech to Digital File Conversion Process

Table 1. Six Sentences Used in Coder Simulations

File Name	Sentence	Speaker	Duration Sec(%)
S1	The pipe began to rust while new	Female	2.43 (79)
S2	Theives who rob friends deserve jail	Male	2.27 (74)
S3	Add the sum to the product of these three	Female	2.67 (85)
S4	Open the crate but don't break the glass	Male	2.11 (69)
S5	Oak is strong and also gives shade	Male	2.30 (75)
S6	Cats and dogs each hate the other	Male	2.11 (69)

infinite number of levels between the file's minimum and maximum amplitude limits. This assumption is reasonable since, when using an 8-bit uniform quantizer, there are 16 possible input values for each quantization level. In this study we will consider quantizers with no more than 256 output levels. The input speech files contain 8 KHz sampled, 3.2 KHz lowpass filtered speech with 12-bits of resolution per sample.

The statistics we require from each sentence are the mean (η), variance (σ_x^2) and amplitude histogram (p_j; $j = 1,2,\ldots,M$). Program SPCHSTAT measures each of these, determines the maximum and minimum amplitudes of the speech, x_{max} and x_{min}, and the total energy in the sentence. M is the number of bins in the histogram. Since the speech is quantized to 12-bits in the speech files, we will consider only histograms with number of bins less than or equal to 4096. Table 2 lists the results of statistics measurements of the six sentences. Since samples in the speech files are represented as two's-complement 16-bit integers, the possible range of amplitudes is -32768 to +32767. Thus, all the numbers in Table 2 are relative to this range. All the measured means (η) are close to zero (<.02 % of 2 x_{max}) and are assumed to be zero for all simulations calculations. A preliminary comparison of the speech files based upon the statistical measures will prove useful in interpreting the speech coder simulations results. Table 3 ranks the sentences from greatest to least, where greatest represents the statistical value of greater magnitude. The numbers entered in the table denote speech file number.

Table 2. Statistics of Six Sentences

Sentence	Mean (η)	Variance (σ_x^2)	Std. Dev. (σ_x)	x_{max}	x_{min}
S1	-1.604	$3.302 \cdot 10^7$	5746	32047	-25695
S2	-3.137	$.934 \cdot 10^7$	3057	28159	-32767
S3	-3.069	$2.833 \cdot 10^7$	5323	28687	-24687
S4	-3.284	$2.884 \cdot 10^7$	5370	27455	-32767
S5	-5.454	$2.310 \cdot 10^7$	4807	24318	-31215
S6	-.416	$1.626 \cdot 10^7$	4032	30287	-22287

Table 3. Ranking of Sentences for Several Parameters

	Greatest					Least
Energy	1	4	3	5	6	2
Variance	1	4	3	5	6	2
Duration	3	1	5	2	4/6	
Mean	5	4	2	3	1	6

Analytical Histograms

Comparisons between the optimum quantizer using a histogram derived from a specific speech utterance and the optimum quantizer using analytically derived histograms were used throughout this study. Four types of analytically derived histograms are considered; 1) uniform, 2) Gaussian, 3) Laplacian and 4) gamma. Optimum quantizers calculated using an analytic histogram are given the name of the histogram function. For example, an optimum quantizer calculated using a uniform histogram will have a uniform quantizer characteristic, and be called a uniform quantizer. Optimum quantizers computed using a speech histogram will be called an optimum quantizer.

Subroutine THTSB is used to generate analytical histograms. Figure 6 shows the characteristics of a Laplacian histogram as an example of the considerations in specifying a histogram. In the case of distributions of infinite extent (Laplacian, Gaussian and gamma), it is necessary to choose some cutoff point on the amplitude (x) axis. For comparative purposes, histograms are constructed with the same variance as the variance measured from a sentence. The count in a given

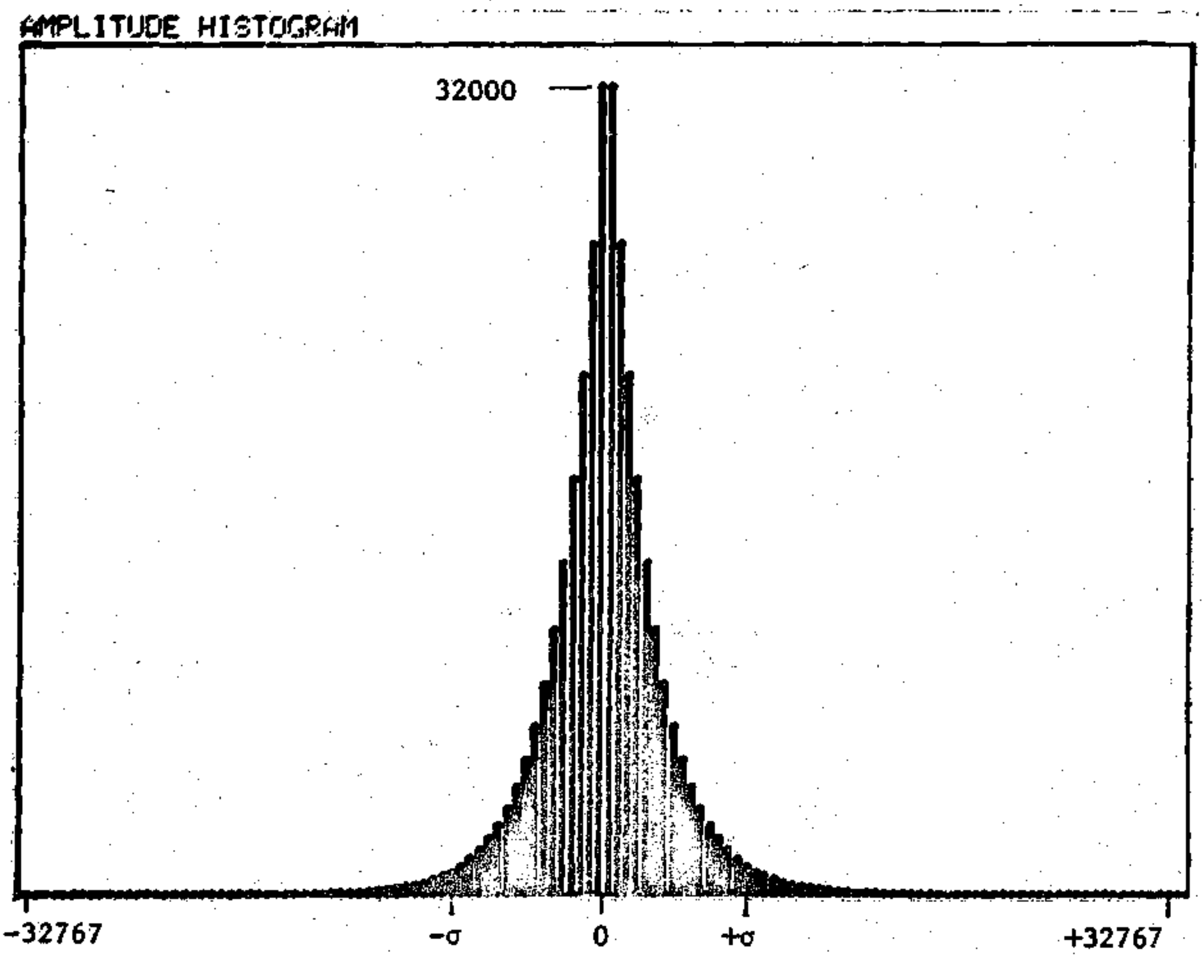


Figure 6. Laplacian Histogram

histogram bin represents the probability of receiving a speech sample within a range of amplitudes defined by the bin edges. Since there are fewer histogram bins than possible input amplitudes, each bin encompasses a range of input sample amplitudes. The count assigned to any bin should be the sum of the counts for all possible amplitudes encompassed by the bin edges. In the analytical histograms computed from Laplacian, Gaussian and gamma distributions, we wish to compute a bin count as the area under the appropriate probability density function curve between points defining bin edges. Each distribution, $p(x)$, has its maximum at $x = 0$. Within the constraints of integer arithmetic, we must restrict the maximum bin count, $p_{M/2}$ to be less than the maximum integer number, thus $p_{M/2} < 32767$. Since the Laplacian and gamma distributions fall off rapidly for $|x| > 3\sigma_x$, we wish to make the $p_{M/2}$ count as large as possible. Under these constraints, we compute the bin count as the area under the density curve, and then scale the area by a constant such that $p_{M/2}$ is as large as possible, thus

$$p_j = K \int_{x_{j-1}}^{x_j} p(x)\, dx.$$

A closed form expression for the area under a Laplacian curve was used for computing bin count in the Laplacian distributed histogram. A closed form expression for the area under the gamma and Gaussian curves is not available, therefore as a simplification, the area was approximated by the amplitude of the density function at the center of the bin multiplied by the appropriate scaling constant. All histograms were computed within the following limits:

1) Maximum number of counts in any bin is 32000.
2) Maximum number of bins is 4096.
3) Range of histogram abscissa is −32768 to +32767.
4) Mean (η) = 0.
5) All histograms are symmetric with respect to x = 0.
6) Minimum allowable variance, σ^2_{min} = (3276.8) .

The following paragraphs describe the histogram generating equations used by THTSB.

__Uniform__. The uniform distribution is used to generate a uniform quantizer. The histogram is given by

$$p_j = 1000 \qquad \text{for} \quad j = 1,2,\ldots,M. \tag{18}$$

__Gaussian__. The Gaussian probability density is [7]

$$p(x) = \frac{1}{\sigma_x\sqrt{2\pi}}\exp\left(\frac{-x^2}{2\sigma_x^2}\right) . \tag{19}$$

In the subroutine THTSB the following scaled form of the Gaussian distribution is used

$$p_j = 32000 \exp\left(\frac{-x_j^2}{2\sigma_x^2}\right) \qquad \text{for} \quad j = 1,2,\ldots,M \tag{20}$$

where M is the number of histogram bins.

Laplacian. A Laplacian distribution found to be a fair model of the amplitude distribution from a large ensemble of speakers [6] is

$$p(x) = \frac{1}{\sigma\sqrt{2}} \exp(\frac{\sqrt{2}\ x_j}{\sigma_x}) \ . \tag{21}$$

The subroutine THTSB gives the histogram bin count for a Laplacian distribution as the area under the distribution curve between bin boundaries. The expression is

$$p_j = 1.0 \cdot 10^7 \ (\exp(\frac{\sqrt{2}\ x_{j-1}}{\sigma_x}) - \exp(\frac{\sqrt{2}\ x_j}{\sigma_x})) \tag{22}$$

$$\text{for} \quad j = 1,2,\ldots,M.$$

Gamma. A gamma distribution that has been found to closely model the amplitude distribution from a large ensemble of speakers [6] is

$$p(x) = \frac{\sqrt{3}}{8\pi\sigma_x |x|} \exp(\frac{-\sqrt{3}|x|}{2\sigma_x}) \ . \tag{23}$$

The subroutine THTSB uses a scaled version of this distribution to determine gamma distribution bin counts as

$$p_j = 64000 \ \sqrt{\sigma_x} \exp(\frac{-\sqrt{3}}{2\sigma_x}(4 + |x_j| \ )) \tag{24}$$

for $j = 1,2,\ldots,M$.

OPT1 Program Description

OPT1 is the main optimum quantizer calculation program. The program performs the functions of histogram generation, quantizer calculation and PCM speech coding. Figure 7 is a flowchart that represents the major options available to OPT1 users. OPT1 requires as input a speech file and the following five parameters:

1) NBIN, number of histogram bins.
2) NLOUT, number of quantizer output levels.
3) CTST, convergence test limit.
4) VAR, speech histogram variance, σ_x^2 from SPCHSTAT.
5) NVAR, number of standard deviations to histogram abscissa limits.

The five OPT1 parameters given here are in terms of mnemonics used in OPT1. These mnemonics are related to expressions used in earlier equations by:

1) NLOUT = N of equation (4)
2) NBIN = M of equation (8a)
3) CTST = C of equation (13)

Several other data are possible to modify the program use. In the Accuracy, Convergence and Parameter Study tests it was desired to calculate several quantizers without retaining the output coded speech file. It was found that using analytical histograms that should produce symmetrical quantizers, a small symmetry error resulted in the placement of quantizer decision and reconstruction levels. It is possible to

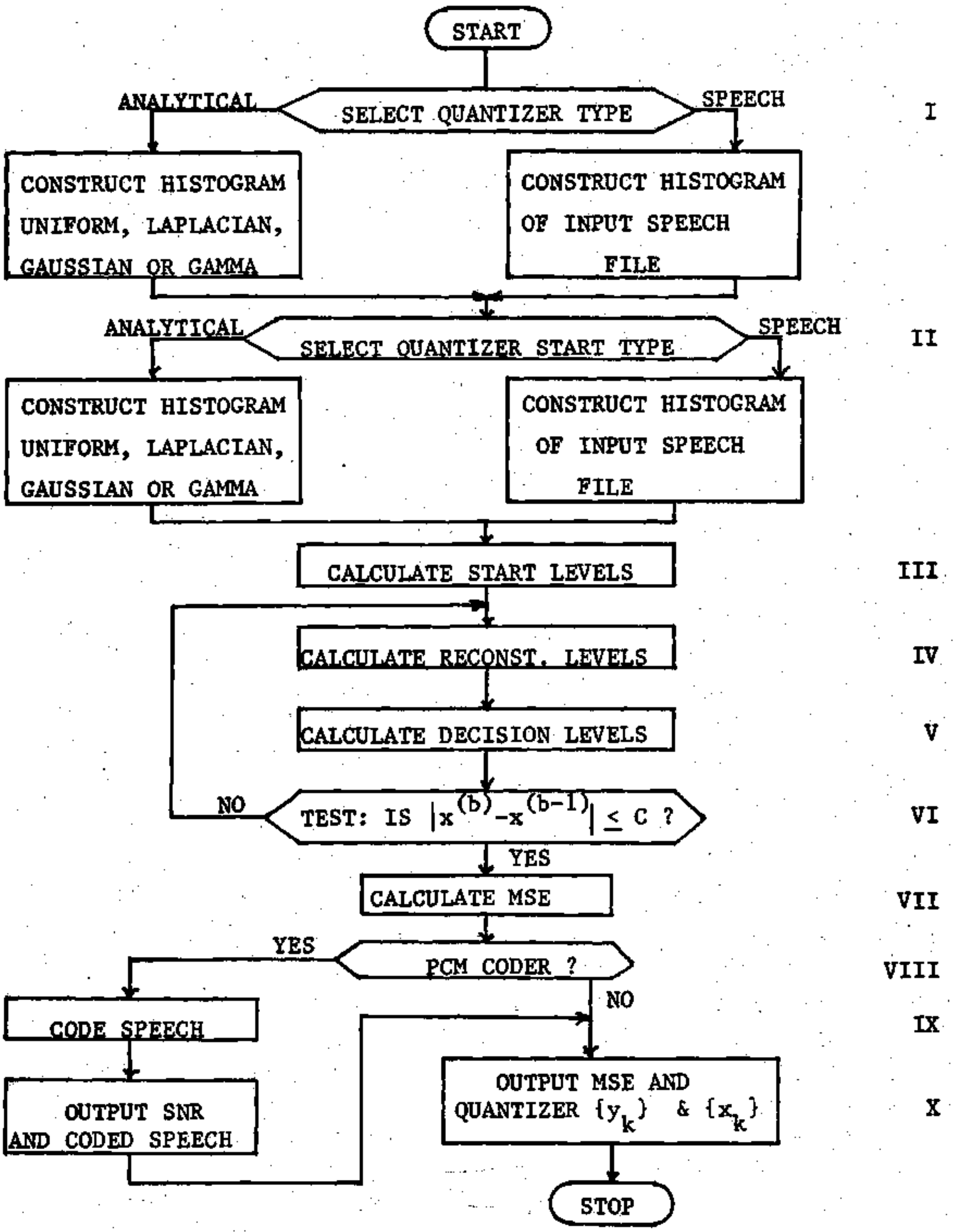


Figure 7. OPT1 Program Flow Diagram

force the N/2 decision level (for N even) or the N/2 reconstruction level (for N odd) to be exactly zero as a means of correcting these errors. This fixed zero option was used in all the quantizer calculations based upon analytical histograms, and was never used for the speech-histogram derived quantizers. From the first two decision blocks on the flowchart, it can be seen that a quantizer may be calculated based upon one histogram type, while having the start sequence determined from a different histogram type. This feature is used on the Convergence tests.

The program OPT1 provides six basic outputs. These are listed below.

1) $\{x_k\}$, the set of N+1 quantizer decision levels.
2) $\{y_k\}$, the set of N quantizer reconstruction levels.
3) NIT, number of iterations to attain desired convergence limit.
4) TIME, time required for NIT iterations.
5) MSE, the mean squared error of the quantizer.
6) SNR, the PCM coded speech signal to quantization noise ratio.

It is important to be able to determine how quickly an optimum quantizer can be calculated. From Figure 7, we see that one iteration is the time required for OPT1 to perform steps IV, V and VI. The number TIME is computed by summing the time required to do steps IV, V and VI over NIT iterations. OPT1 requires some computational overhead to input data, measure statistics and provide for programming choices. In the comparative study of optimum quantizer calculations, only the iteration time is considered. As will be shown in Chapter IV, TIME depends upon choice of NBIN and NLOUT and the resultant NIT.

The quantizer mean squared error is calculated by two methods in OPT1. The first calculation uses equation (14) and is performed in step VII as shown on the flowchart. This MSE calculation is based on the histogram distribution and is used in the comparisons of the Accuracy, Convergence and Parameter Study tests where actual speech based quantizers are not being considered. The use of this calculation will be denoted by an H subscript to the name as, MSE_H. The second MSE calculation is performed with the coder output SNR calculation using the expression

$$MSE_F = \frac{1}{L} \sum_{j=1}^{L} (y_j - x_j^2) \tag{25}$$

where L is the number of samples in the speech file, x_j is the j^{th} quantizer input sample and y_j is the j^{th} quantizer output sample. This MSE calculation is used only when quantized speech files are to be compared as in the PCM and ADPCM coder simulations. As shown in (25), this calculation will be denoted by MSE_F.

CHAPTER IV

OPT1 PROGRAM TEST RESULTS

Three groups of tests were performed to characterize the operation of OPT1. Initially, it is important to show that the quantizers calculated by OPT1 are indeed minimum mean squared error. This will serve to add credibility to the conclusions. Also, we must know what combinations of input parameters result in an acceptable amount of MSE minimization in a minimum amount of time.

Accuracy Test Results

The algorithm Accuracy tests were performed to provide documentation showing that speech related quantizers calculated by OPT1 compare closely (in MSE calculation results and location of quantization levels) with previously published results. In the cases of uniform and the simpler Laplacian quantizers, theoretical results were calculated to aid in the comparisons. We wish to give reasonable confidence in the accuracy of OPT1 results using speech inputs by showing that the program works well using histograms with distributions similar to those of real speech. As an indirect result of these tests, it will be shown that there is disagreement in all of the published results we have considered. For the purpose of this study, we assume that if quantizers are calculated by OPT1 using uniform, Gaussian, Laplacian and gamma distributions compare closely with the published results of Max [1], Paez and Glisson [4] and Esteban et al. [3], then the extension to speech-histogram quantizers will also be minimum mean squared error. Comparisons were based upon MSE_H and by considering location of the quantizer's decision and reconstruction levels.

The Accuracy tests consist of the calculation of quantizer characteristics and MSE_H with uniform, Laplacian, Gaussian and gamma distributions. The histograms used as the input signal distributions were also used in the maximum entropy start sequence calculations and the MSE_H calculations. Quantizers of 2, 4, 8, 16, and 32 output levels were calculated for each distribution type using the program parameters;

1) Number of histogram bins, NBIN = 4096
2) Convergence test limit, CTST = 0.5.

The CTST parameter choice implies that the iterations for any quantizer will terminate when all decision levels change (from the previous iteration) by less than 3.1 % of the minimum histogram bin width. Distributions for the Laplacian, Gaussian and gamma quantizers assumed a zero mean and a standard deviation one tenth of the maximum input signal range. With the maximum count in any histogram bin limited to be less than 32000, this standard deviation value caused some of the bins representing maximum and minimum input signal amplitudes to have zero counts. It should be noted from Table 2 in Chapter III that the standard deviations estimated from six sentences range from 3057 to 5746. The value of $\sigma_x = 3276.8$ used in the Accuracy tests lies within this range. From Table 2, we see that the input signal histograms span the entire amplitude range (-32768 to 32767) in 5.98 σ_x to 10.78σ_x, depending upon which sentence histogram is used. Through experimentation it was shown that the MSE_H and quantization level locations changed very little as the histogram standard deviation (for Laplace, Gaussian and gamma) was increased from 3276 to 8192. For large σ_x (>8192) where the input amplitude range was covered by less than $4\sigma_x$, it was found that truncation of the distribution caused unacceptable errors in the MSE and quantization level results. We can conclude that the choice of $\sigma_x = 3276.8$ for the Accuracy tests gives reasonable results in which distribution truncation errors should not contribute to any discrepancies. All histograms were constructed with NBIN uniformly spaced count bins for each amplitude between -32768 and +32767.

The Accuracy test results indicate some error in the symmetry of the resultant quantizer characteristics. All quantizer calculations by OPT1 for this test used the fixed zero option described in Chapter III, which fixes the N/2 decision or reconstruction level exactly to zero. All four analytical histograms used in the Accuracy tests are symmetrical with respect to x = 0. Due to the symmetry, we would expect

$$|x_{k-a}| = |x_{k+a}|$$

where $\quad k = \dfrac{\text{NLOUT}}{2}$ for NBIN even

and $\quad$ a is some integer < k.

Similarly, all the resultant reconstruction levels of the quantizer will be paired also. An average percent difference in decision and reconstruction level locations is computed to quantify the amount of symmetry error resulting from the difference in paired level locations not being zero. This calculation for a quantizer of an even number of levels is given by

$$e_s = \frac{100}{N} \sum_{k=1}^{N/2} \left\{ \left| \frac{|y_k| - |y_{N+1-k}|}{|y_k|} \right| + \left| \frac{|x_k| - |x_{N+2-k}|}{|x_k|} \right| \right\} \tag{26}$$

where the y_k are quantizer output reconstruction levels and the x_k are quantizer input decision levels. A value of $e_s = 0.0$ indicates perfect symmetry in the resultant quantizer. Table 4 indicates the results of these calculations for all the quantizers tested. Notice that all errors are less than 0.06 %. The signs indicate the direction of average shift, negative implying all levels are more negative than they would be if the quantizer had perfect symmetry. All individual components of the average, e_s were quite close to the final result. From these results we can conclude that OPT1 introduces an insignificant symmetry error in calculating quantizer decision and reconstruction levels. The table suggests that quantizers constructed from histograms similar to a gamma distribution (as is speech) will be more symmetrical. Also, as the number of quantization levels increase above 32, the error is quite similar for all types of histograms. The symmetry errors are a direct result of errors in reconstruction level locations. Each decision and reconstruction level location is computed independent of the levels not adjacent to it. There is no mechanism in the optimum quantizer algorithm for an error in the x_{k-a} level to generate an equal

Table 4. Average Quantizer Symmetry Percent Error

Number Of Levels	Distribution Type Uniform	Laplace	Gamma
3	+.05	-.011	-.005
4	+.06	-.015	-.007
7	+.06	-.039	-.019
8	+.06	-.042	-.015
15	+.05	-.005	+.015
16	+.046	-.004	+.017
31	+.027	+.012	+.018
32	+.019	+.008	+.019
63	+.022	+.032	+.039
64	+.037	+.033	+.041

and opposite error in the x_{k+a} level.

Table 5 presents a comparison of the Accuracy test MSE results. The uniform quantizer MSE is compared with theoretical MSE as derived in Appendix B. There is only a negligible difference between the OPT1 and Esteban results for a Gaussian distribution. This is to be expected since the same algorithm was used in both calculations. There is a little less agreement with the Max results, but OPT1 results are within 0.4 % of every Max calculation. Since the disagreement is always in the same direction, some of the error is due the representation of the distribution, variance, or distribution cutoff points. Calculations using the Laplacian probability density function, rather than the Laplacian histogram were made to determine the two and four level Laplacian quantizer characteristics. These calculations are included in Appendix C. Even though Laplacian is the only easily integrable distribution we considered, a closed form solution to the quantizer equations was still not possible and calculations did not extend to greater than four output levels. It is interesting to note that the Paez and Glisson MSE results are closer to the theoretical than the other two table entries. This is rather misrepresentative however since the MSE computed from the actual quantizer reconstruction and decision levels given in the Paez and Glisson paper do not yield the same MSE value as shown in their paper. A set of tables is included in Appendix E comparing quantizer reconstruction and decision levels for many different distributions and number of levels. From these tables it can be seen that the OPT1 and Esteban results for Laplacian two and four level quantizers are quite close to the theoretical results. We must

Table 5. Algorithm Accuracy Test Results

Quantizer Distribution	Source	Quantizer Output Levels 2	4	8	16	32
Uniform	OPT1	8.3326	2.0832	.5208	.13021	.03256
	Theoretical	8.3333	2.0833	.5208	.13020	.03255
Gaussian	OPT1	.3630	.1173	.03446	.009461	.002491
	Max	.3634	.1175	.03454	.009497	.002499
	Esteban	.3626	.1172	.03448		
Laplacian	OPT1	.4961	.1735	.05280	.01457	.00378
	Paez & Glis.	.5000	.1765	.05480	.01540	.00414
	Esteban	.4981	.1746	.05350		
	Theoretical	.5000	.1762			
Gamma	OPT1	.6606	.2258	.0664	.0176	.00448
	Paez & Glis.	.6680	.2326	.0712	.0196	.00520

Results are quantizer MSE values

conclude that the apparent divergence in OPT1 MSE values from Paez and Glisson MSE values for quantizers of greater than four levels may not indicate errors on the part of OPT1. Similarly, all OPT1 MSE results are less than the corresponding Paez and Glisson results for the Gamma distributed quantizer. It is possible that Paez and Glisson used different distributions and variances. Figure 8 is a graph of percent difference in MSE value as a function of number of quantizer output levels. All differences were computed relative to the OPT1 results and therefore do not represent differences from any theoretically correct value. From the graph two trends can be observed. First, the results of all quantizer calculations tend to diverge from the OPT1 results as the number of output levels increase. The only inconsistency is the Gaussian distributed quantizer in which the MSE values are shown to converge with increasing number of output levels. The second trend is related to the groupings by distribution type. The MSE difference appears to increase as the distribution type becomes more peaked around zero. The two curves comparing Paez and Glisson results exhibit the largest error which could be due to differences in representing the probability density function. Figure 9 is a comparison of the percent average difference of quantizer decision and reconstruction levels as compared with OPT1 results. For both Figures 8 and 9, continuous curves are used only to collect data points into easily identifiable groups. Due to the discrete nature of abscissa entries, a continuous curve is not meaningful from an interpolation point of view. The error between OPT1 and both Max and Esteban results is generally less than 1.0 % for all cases considered. For the uniform quantizer, differences are all

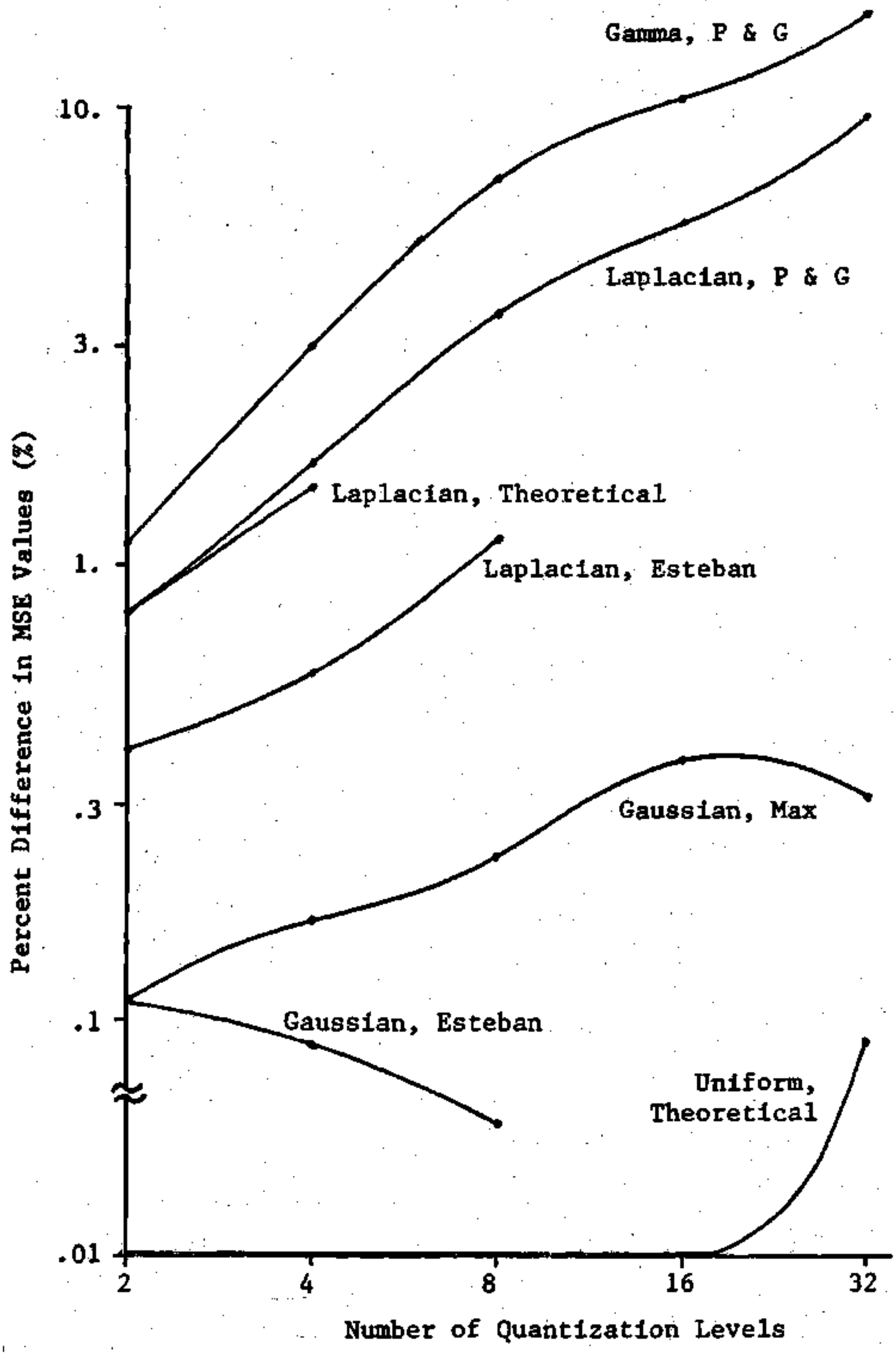


Figure 8. Percent MSE Error Relative to OPT1 Results

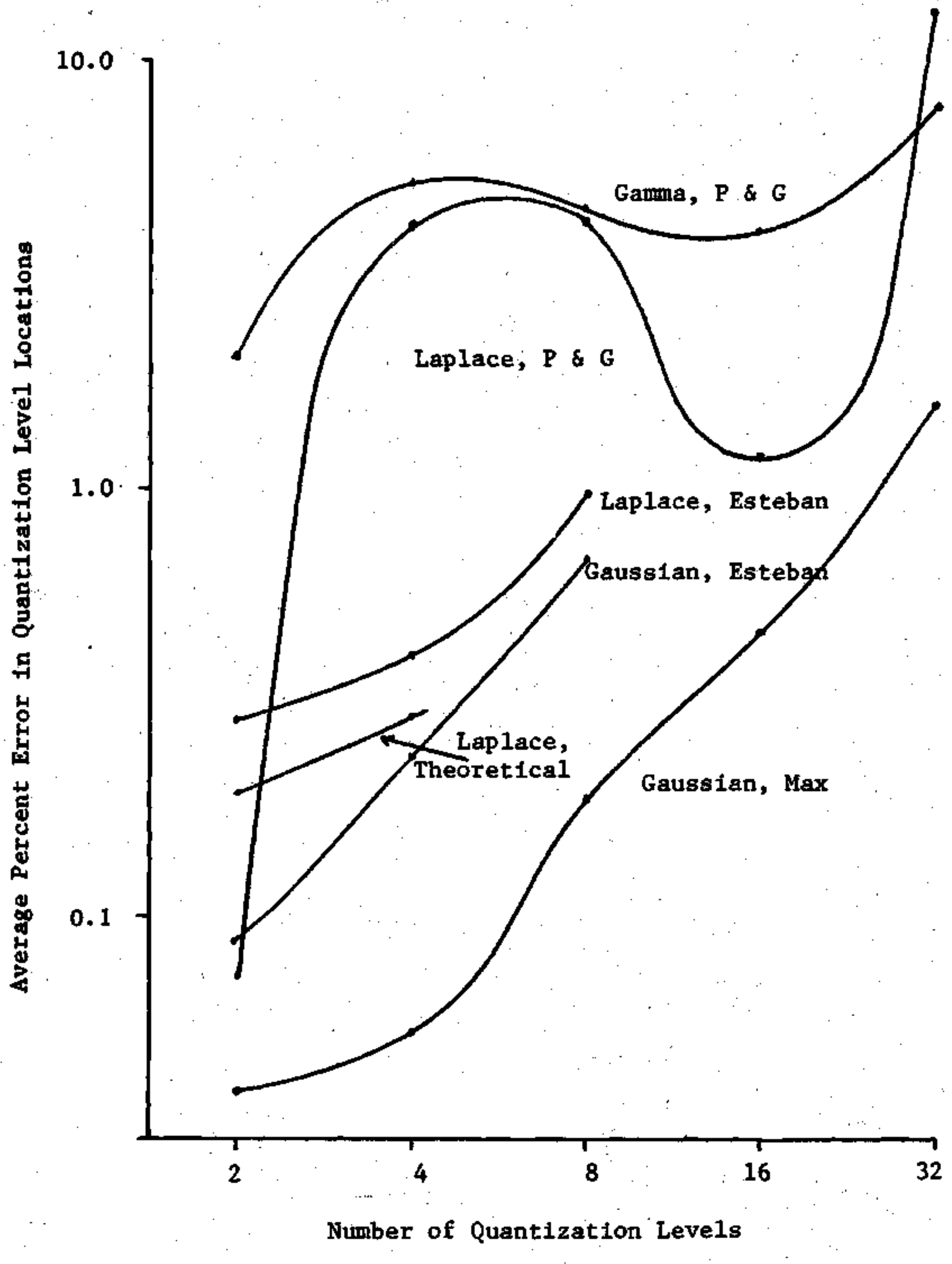


Figure 9. Percent Average Level Error Relative to OPT1 Results

less than 0.01 %. The Accuracy test indicates that OPT1 can compute quantizer characteristics that are very similar to those published by other researchers. Since no one has an exact solution to many of the minimum mean squared error problems considered here, a measure of absolute accuracy is not possible. It does appear that accuracy of results decreases as the rate of change of probability density function increases, as in the gamma distribution.

Convergence Test Results

The Convergence tests were performed to illustrate the manner in which successive iterations of OPT1 converge upon the minimum MSE solution. The results of these tests indicate that the quantizer MSE is minimized with each iteration of the algorithm. Rate of convergence is shown to provide data for the choice of CTST, the program convergence limit parameter. Use of CTST by OPT1 is explained in equation (13). The algorithm dependence upon start sequence choice was also investigated to determine any change in convergence rate with respect to choice of start sequence.

The Convergence tests consist of calculations of uniform, Laplacian, gamma and speech-histogram distributed quantizers using all reasonable start sequence types. Table 6 lists the quantizer type and start sequence combinations for which 2, 4, 8, 16 and 32 level quantizers were calculated. As an example, one set of convergence data was obtained by computing the characteristic of a gamma quantizer that was started with a Laplacian maximum entropy start sequence. Thus, in these tests, we used maximum entropy start sequences (of the appropriate

Table 6. Convergence Tests

Start Sequence Type	Quantizer Distribution Type Uniform	Gaussian	Laplacian	Gamma	Optimum
Uniform	X	X	X	X	X
Laplacian	X	X	X	X	X
Gamma	X	X	X	X	X
Optimum					X

number of quantization levels) from all the available histogram distributions to start the iterations of each type of quantizer. For all calculations not involving speech histograms, NBIN = 4096 and the fixed zero option of OPT1 was enabled. The fixed zero option was disabled for the speech histogram quantizers. Since all the speech histograms had non-zero means, it was assumed that the N/2 decision level (N even) would be slightly different from zero, thus we did not want to induce any aritficial error due to a fixed zero. All quantizer calculations were allowed to run for 700 iterations with MSE_H and the convergence limit, DMIN output at each iteration. The minimum convergence limit, DMIN was actually the maximum C calculated by (13) for all values of k at each iteration. All analytical histograms assumed zero mean and $\sigma_x = 5746$, the standard deviation of sentence S1. For the speech-histogram quantizers, the histogram of sentence S1 was used. MSE values calculated in these tests will differ slightly from the results in Table 5 due to the different choice of σ_x and a greater number of iterations for the convergence test results.

Test results are presented in Figures 10, 11, 12 and 13 as graphs of the calculated quantizer MSE_H as a function of iteration number for quantizers of 4, 8, 16 and 32 levels. Graphs of 2 level quantizers have not been included due to their simplicity. Information on the 2 level quantizer convergence may be seen in Appendix E, Tables A1 and A2. On each set of axis the MSE_H of one quantizer type for several start sequence types are given. Along the ordinate of each graph is plotted the maximum MSE value (occurring at the first iteration, or due to the maximum entropy quantizer) and the minimum MSE_H value from the 700^{th}

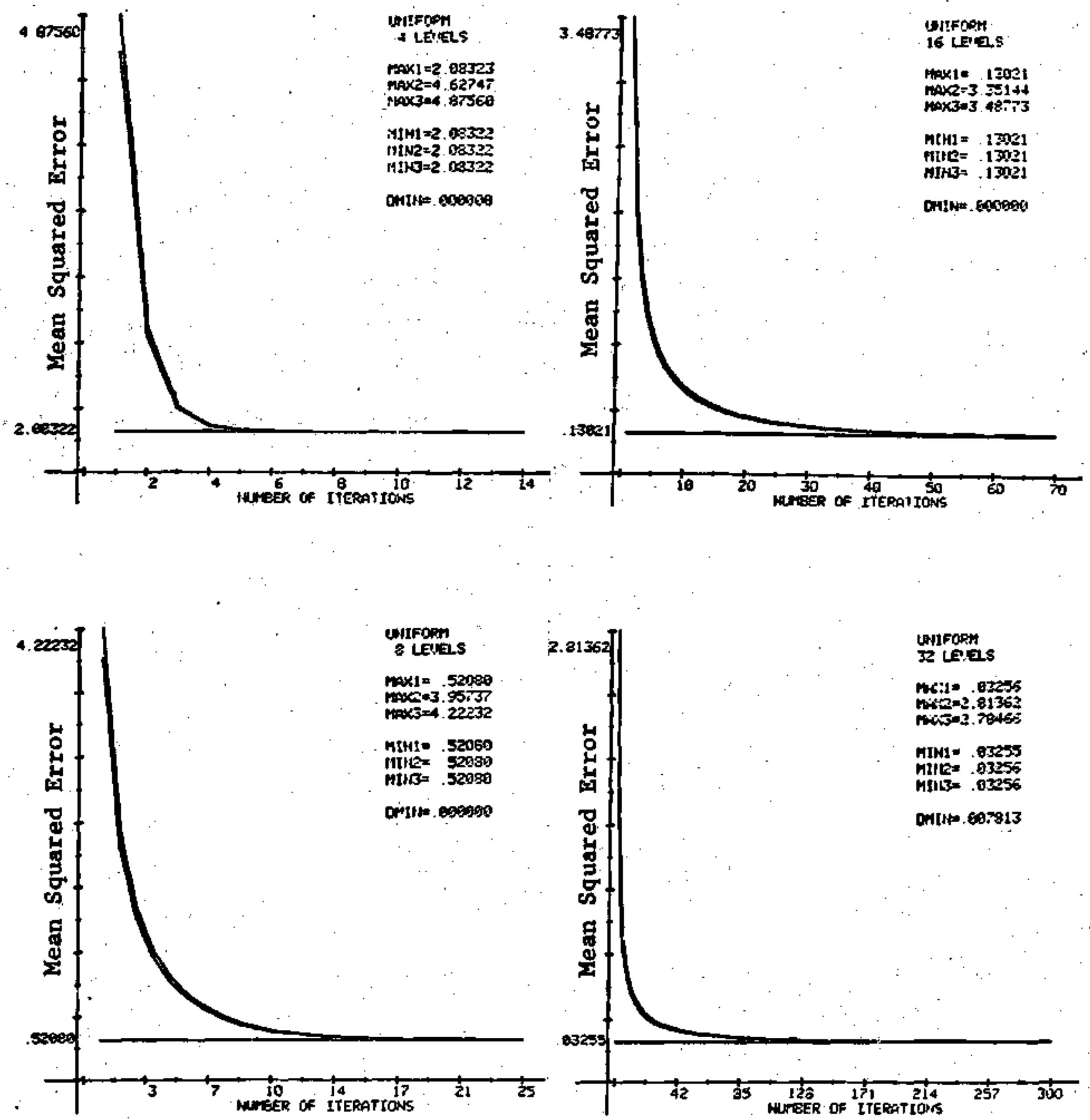


Figure 10. OPT1 Convergence of a Uniform Distributed Quantizer

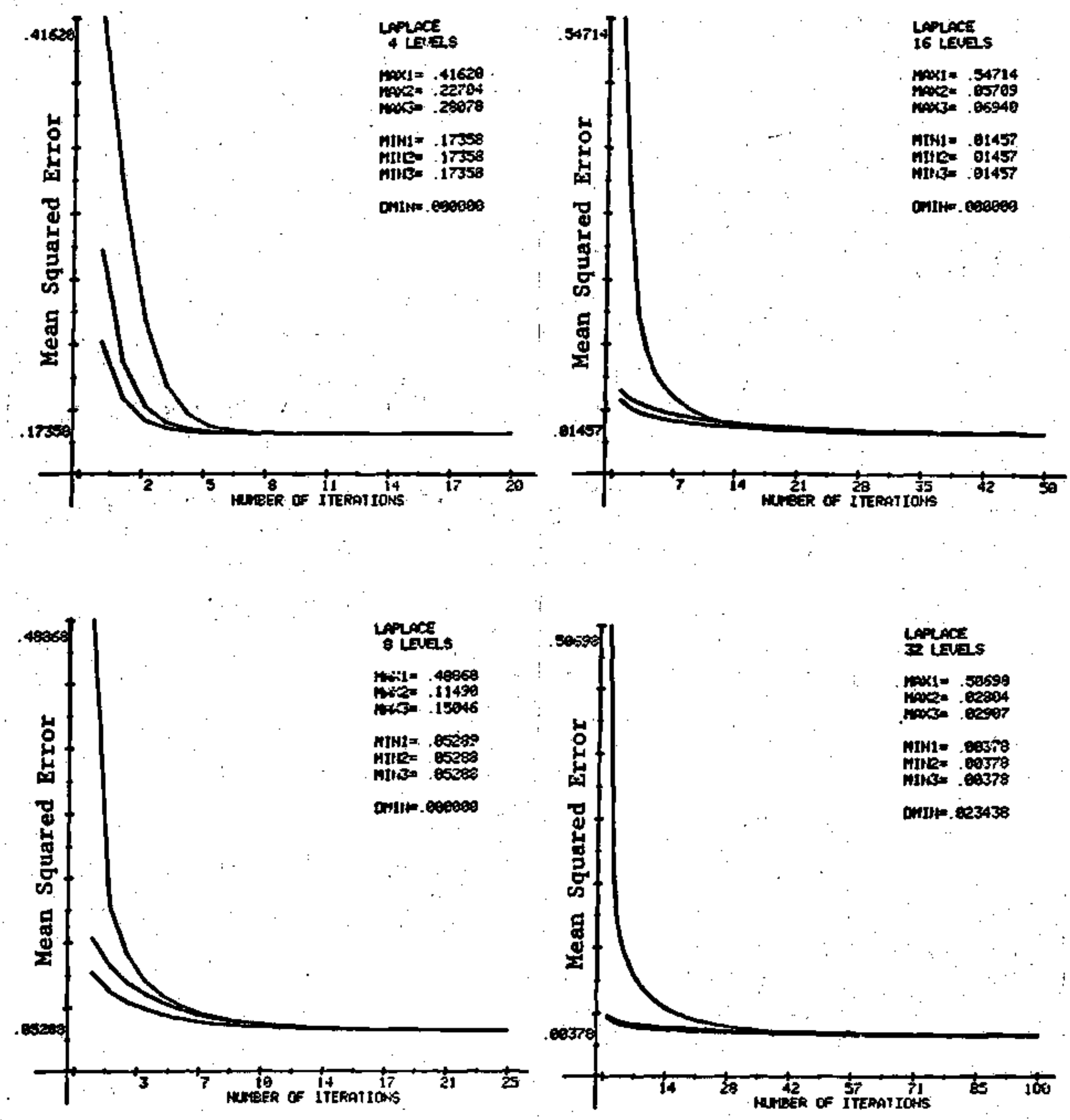


Figure 11. OPT1 Convergence of Laplacian Distributed Quantizers

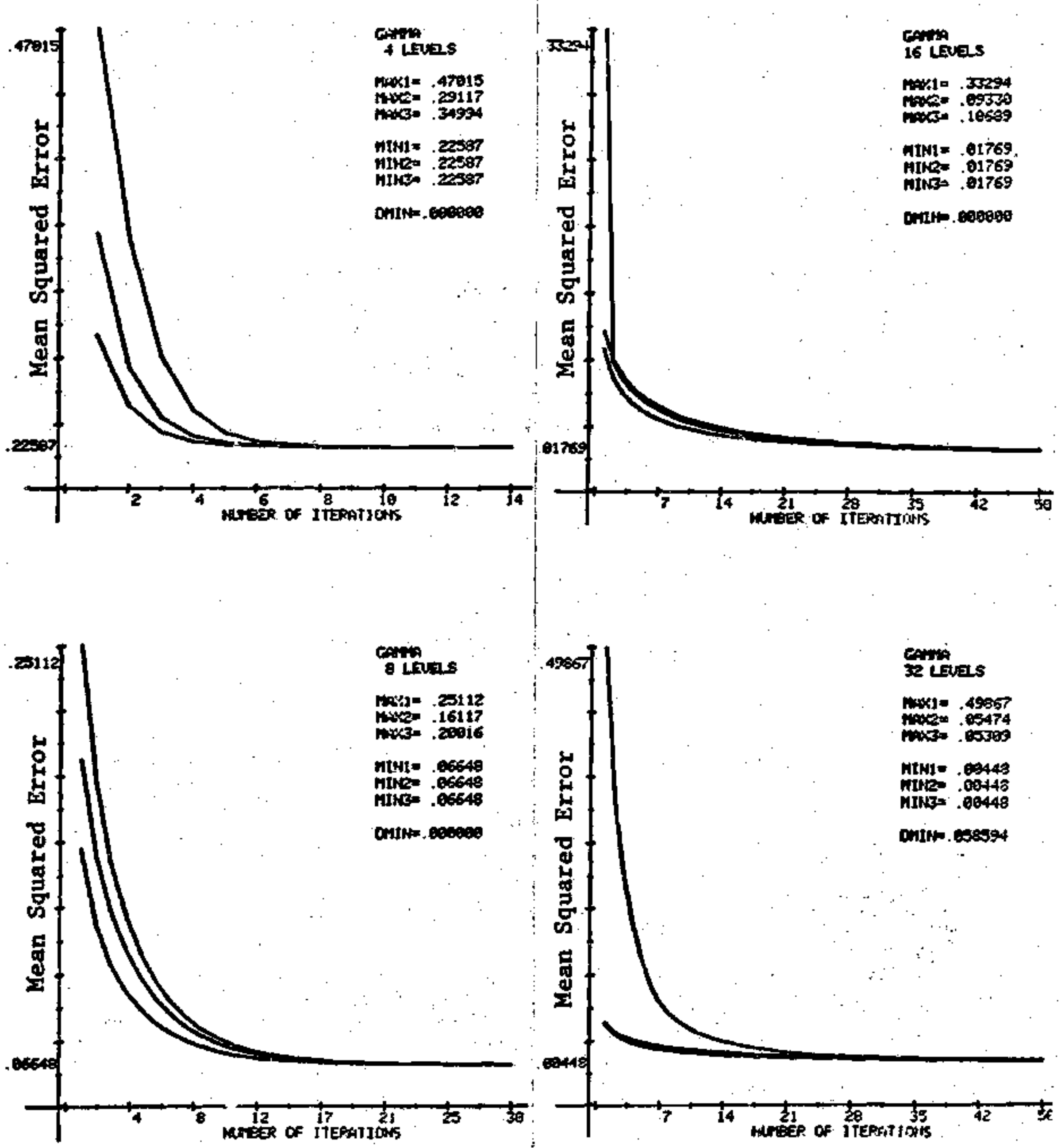


Figure 12. OPT1 Convergence of Gamma Distributed Quantizers

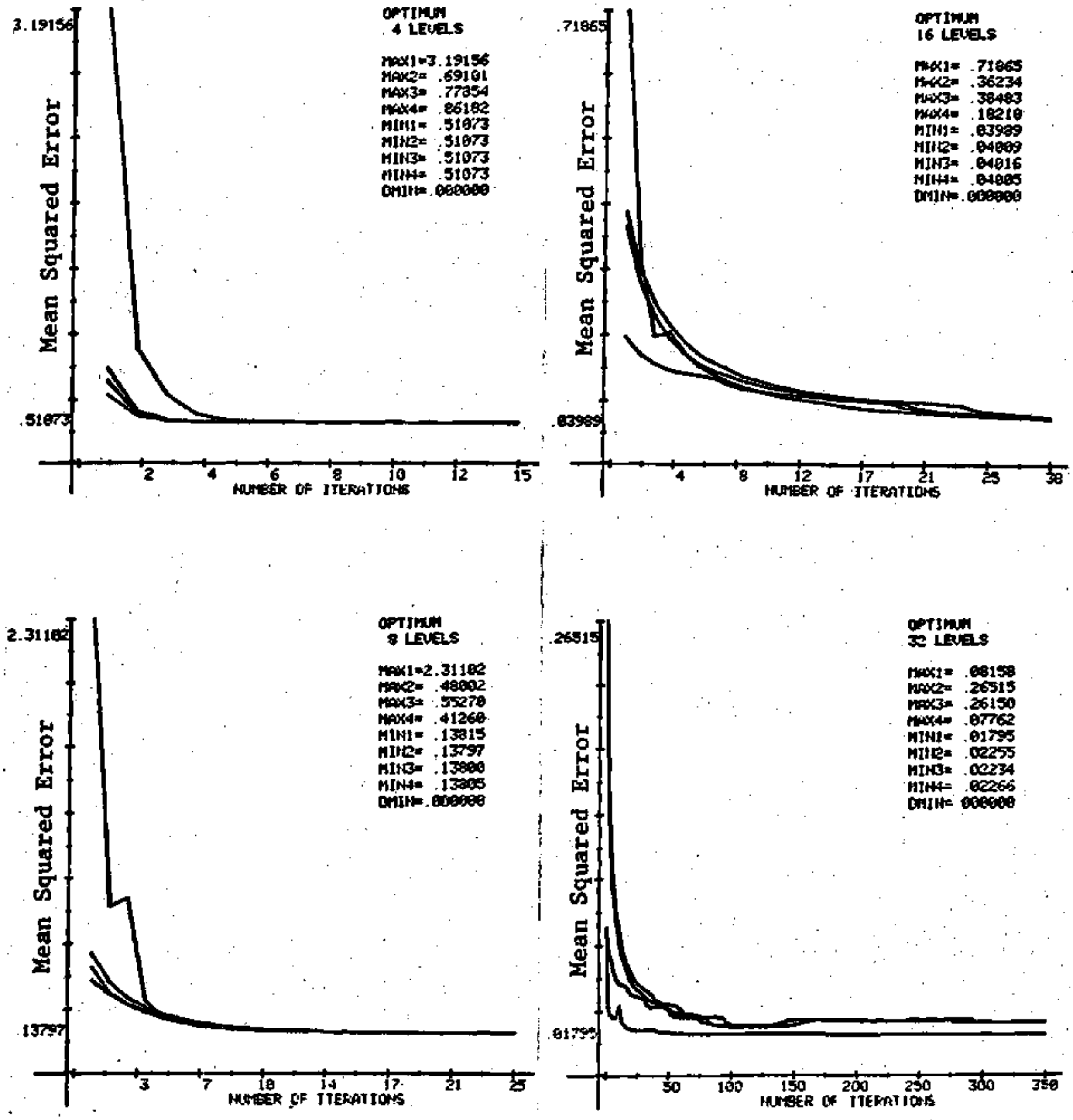


Figure 13. OPT1 Convergence of Optimum Distributed Quantizers

iteration of the algorithm. Along the abscissa is plotted NIT, the number of algorithm iterations. When DMIN = 0.0 the algorithm had converged as closely as the histogram would allow to the minimum MSE quantizer solution and hence no change in MSE occurred past that point. In the graphs, the NIT axes are scaled such that they cut off after no appreciable change in MSE occurs for each additional iteration. At this point it is assummed that the quantizer MSE has been minimized as much as the histogram would allow.

Each axis in Figures 10, 11 and 12 has 3 curves on them and printed endpoint values of MAX1, MIN1, MAX2, MIN2, MAX3 and MIN3. For all quantizer distributions MAX1 and MIN1 refer to the maximum and minimum MSE values calculated using a uniform histogram start sequence. Similarly, MAX2 and MIN2 refer to MSE values resulting from the use of a Laplacian start sequence. And MAX3 and MIN3 are the MSE values for calculations using a gamma start sequence. In Figure 13, MAX4 and MIN4 give the endpoint MSE values for calculations using a speech histogram start sequence. Each graph in Figure 13 has four curves on it, the fourth one representing calculations using the speech-histogram start sequence. The DMIN value printed on each graph is the largest DMIN calculated on the 700th iteration over all start sequence types plotted. DMIN is the CTST value that would have caused the algorithm to terminate by the 700th iteration. Tables A1 and A2 in the Appendix present the curve endpoint MSE and DMIN values for each locus in Figures 10, 11, 12 and 13. Additional table entries list the iteration number beyond which DMIN = 0.0. Tables A3, A4, A5 and A6 present data used in the choice of an optimum CTST value. Table entries represent the percent difference from the MSE at the 700th iteration of the MSE calculated at the indicated DMIN value.

Qualitatively, all the graphs in Figures 10, 11, 12 and 13 support the notion that MSE decreases with each iteration of OPT1. Also, we can see that regardless of what start sequence was used, the same MSE minimization occurred. From Figure 10 we note that the maximum entropy quantizer of a uniform distribution is exactly the same as the minimum MSE quantizer. The uniform-started (maximum entropy start sequence computed from a uniform histogram) uniform quantizer achieves the minimum possible DMIN value in approximately 75 % of the number of iterations required for other start sequences. The curves of Figure 11 indicate the Laplace-started optimum quantizer begins the iteration process much closer to the minimum MSE value than the uniform or gamma start sequences. It can be seen that the 2, 4, 8 and 16 level quantizers all reach the minimum MSE result in approximately the same number of iterations. The 32 level quantizer shows a large difference between uniform started and Laplace or gamma started quantizers. The gamma distributed quantizers of Figure 12 exhibit convergence characteristics quite similar to those of the Laplacian quantizers. For the 2, 4, 8 and 16 level quantizers the Laplace-started quantizers appear to converge more rapidly than the gamma-started gamma quantizers. In the 32 level quantizer, we see that the gamma started quantizer converges more rapidly than quantizers using the other two start sequences. The speech-histogram quantizers of Figure 13 show several interesting phenomena that were not present in the previous figures. Table A2 will aid in observing what the algorithm does. All five quantizers converge upon the minimum MSE solution in less than 350 iterations. The 4 and 8 level quantizers converged more rapidly than the comparable Laplacian or gamma quantizers. Convergence of the 16 and 32 level optimum quantizers was much slower than the comparable Laplacian or gamma quantizers. In the tests using 8, 16 and 32 quantization levels, convergence is not as smooth as in the other tests. This is quite noticable in the 32 level case where the MSE oscillates about a decreasing mean value. The presence of this oscillation supports the use of CTST as an algorithm halt test rather than testing for the minimization of the MSE. With enough iterations, in this case for NIT > 300, the oscillations cease and the MSE has been minimized as much as possible with the data. Notice that for all four graphs in Figure 15,DMIN attained a minimum value of 0.0, suggesting that the greatest amount of minimization possible with the supplied histogram was achieved. The data presented in this test indicates that the OPT1 program will converge upon the minimum MSE quantizer more rapidly when the algorithm uses the start sequence computed from the same histogram as the quantization levels are computed from.

We see from the MSE convergence graphs that the slope of the curves decreases (approaching 0) as the number of iterations increase. It is reasonable to expect little change in MSE beyond a certain number of iterations. Tables A3, A4, A5 and A6 contain data from which a choice of CTST is made. If D is the percent difference in MSE at a given CTST value with respect to the minimum MSE, the range of D for several choices of CTST is found to be:

$$\begin{aligned} CTST &= 10.0; \quad 0.005 < D < 7.4 \\ CTST &= 1.0; \quad 0.00009 < D < 0.08 \\ CTST &= 0.1; \quad 0.0 < D < 0.01 \end{aligned} \tag{27}$$

From these results we see that a choice of CTST = 1.0 would insure a MSE minimization to at least 0.08 % of the minimum possible MSE value. A decrease in CTST would result in a quantizer closer to the optimum, but at the expense of more iterations for a small change in MSE. A choice of CTST = 10.0 could result in a quantizer with a MSE more than 7 % greater than its possible minimum value. As a general rule, we would suggest a choice of CTST = 1.0 for applications where speed is important, and excess iterations cannot be tolerated. A choice of CTST = 0.1 to 0.5 would be advisable for applications where accuracy is important. One trend that should be noticed is that the D increases as number of quantization levels increase for any given CTST value. One can expect the following algorithm performance on a speech-histogram quantizer calculation:

NUMBER OF LEVELS	NUMBER OF ITERATIONS
4	15
8	50
16	180
32	300

A value of CTST = 0.5 is used throughout the remainder of this study to provide relatively accurate results in a reasonable number of iterations.

OPT1 Parameter Study

A study of OPT1 was conducted to determine a set of rules for the selection of OPT1 parameters that would provide the most rapid, accurate calculation of a desired quantizer characteristic. As a result of these tests, some limitations on the choice of parameters were characterized and an estimate of calculation time was determined. The three basic optimum quantizer calculation program parameters are NBIN (number of amplitude bins in histogram), NLOUT (number of quantization levels at quantizer output) and CTST (convergence limit test value). NLOUT will be determined by the quantizer application and is not a parameter we are free to choose. CTST was discussed in the previous convergence test section and will be only briefly discussed here. Upper and lower bounds on the choice of NLOUT and NBIN will be given based upon the test results. We will also present a relationship for estimating the algorithm calculation time based upon various parameter choice combinations.

The parameter study consisted of the calculation of quantizer characteristics using uniform and gamma amplitude probability distributions. The gamma histograms were constructed with $\sigma_x = 5746$, the variance of sentence S1. All quantizer calculations used the maximum entropy start sequence from the given histogram. Quantizers of 2 to 256 levels, were calculated using all possible combinations of the following CTST and NBIN parameter values:

NBIN = 128, 256, 512, 1024, 2048, 4096

CTST = 10.0, 5.0, 1.0, 0.5, 0.1, 0.05, 0.01

Each quantizer was calculated first with the fixed zero option enabled, then with the option disabled. To limit the amount of time required for the creation of our data base, the number of algorithm iterations was limited to 1000. If the CTST was not satisfied after 1000 iterations, the algorithm would terminate. Table A7 lists the cases where this limitation caused early termination of the algorithm. The table indicates that most uniform quantizers were computed with CTST $\geq$ 0.01 and most gamma quantizers with CTST $\geq$ 1.0 in 1000 iterations of OPT1. For each quantizer, computed values were recorded for quantizer MSE_H as computed by equation (14), SNR of PCM coded speech file S1, number of algorithm iterations (NIT) to the minimum MSE quantizer solution and the computation time (TIME) for NIT iterations of the algorithm. The characteristics for a total of 2520 optimum quantizers were computed to provide the data base used in this study.

Initially, we will assemble the test results into four groups based upon histogram type. These groups are; 1) gamma distributed histogram with fixed zero option enabled in OPT1, named gamma fixed, 2) gamma histogram with fixed zero option disabled, named gamma float, 3) uniformly distributed histogram with fixed zero option enabled, named uniform fixed, and 4) uniform histogram with fixed zero option disabled, named uniform float. Figures 14 and 15 present SNR as a function of number of quantization levels. The data in Figure 14 represent SNR at the output of a PCM coder operating upon sentence S1. The following expression was used for the SNR computation:

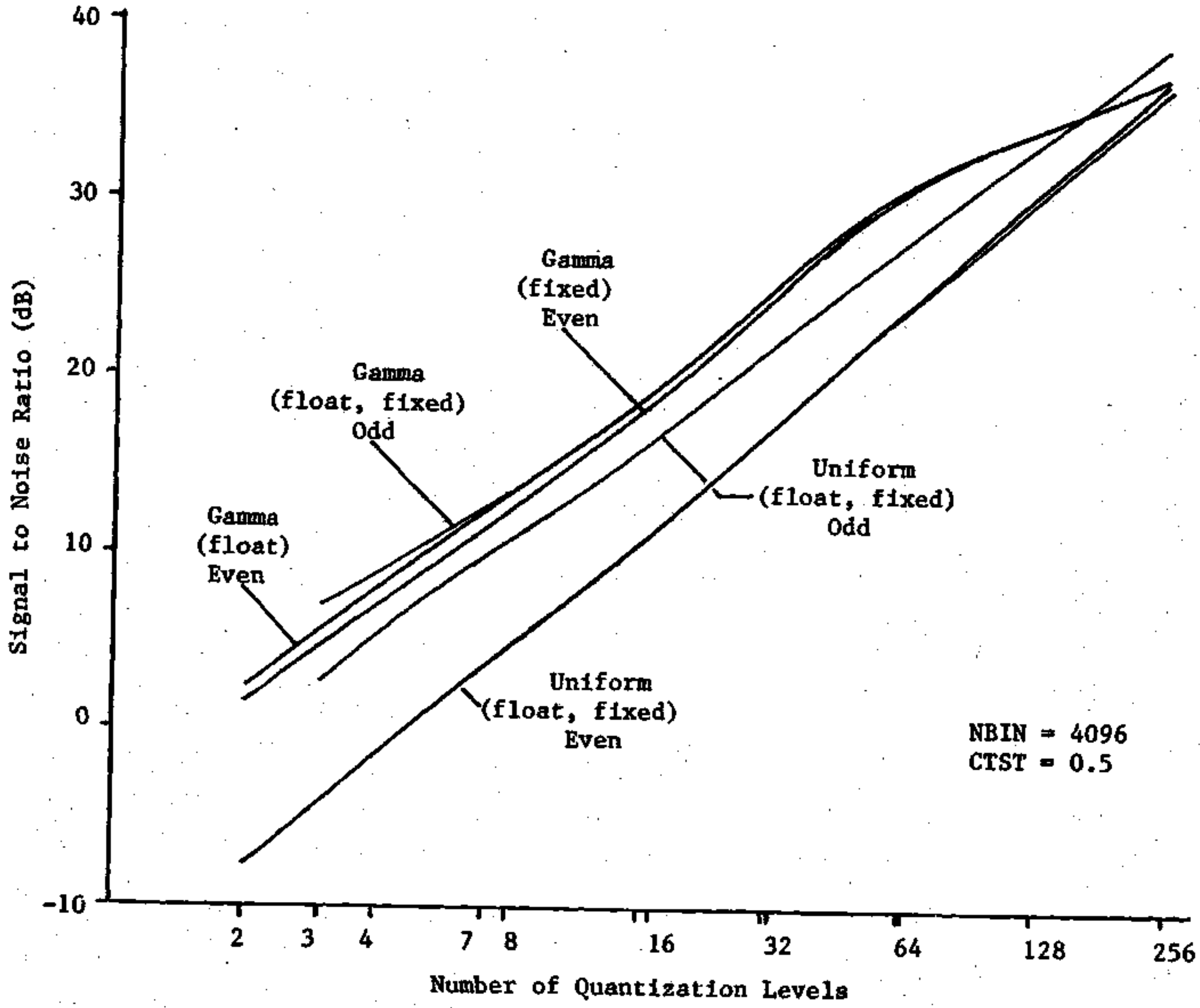


Figure 14. SNR from PCM Coding of Sentence S1

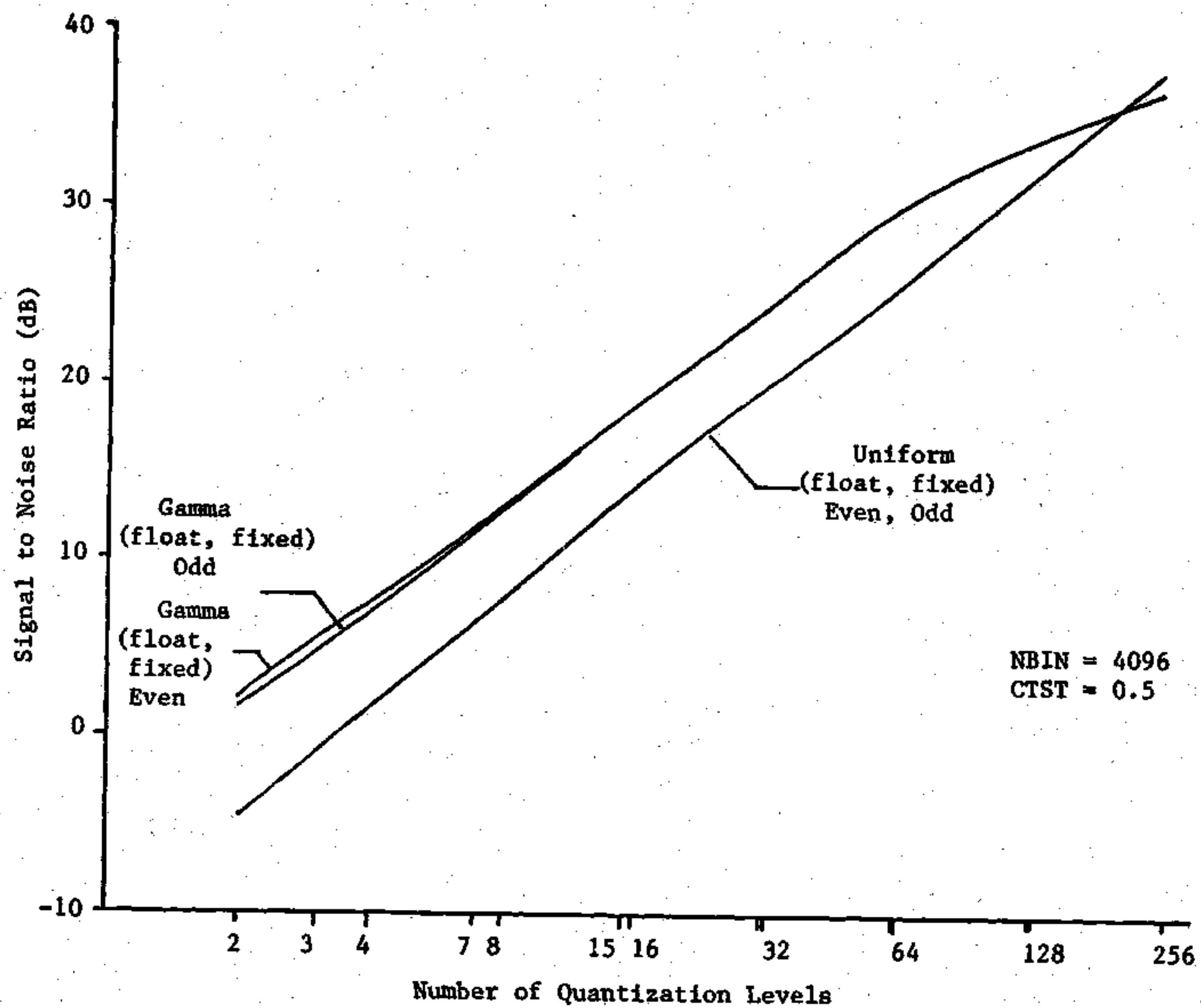


Figure 15. SNR Computed from MSE Output of OPT1

$$SNR_F = 10 \operatorname{Log}_{10} \frac{\sum^{L} x^2(n)}{\sum^{L} e^2(n)} \tag{28}$$

where L is the number of samples in the speech file (here, L = 24576), x(n) is the coder input signal and is the quantizer error signal. Equation (28) is similar to (16). It should be noted that this SNR measure is quite dependent upon the statistics of the signal to be coded and quantifies how well a quantizer performs on a particular input signal. In contrast, the data in Figure 15 was computed from the quantizer MSE value as output by OPT1. This SNR was computed using

$$SNR_Q = 10 \operatorname{Log}_{10} \left\{ \frac{1}{\sum_{k=1}^{N} \sum_{j=x'_{k-1}}^{x'_k} (y_k - x'_j)^2 p_j} \right\} \cdot \left\{ \frac{\sum_{j=1}^{M} (x_j - \eta)^2 p_j}{\sum_{j=1}^{M} p_j} \right\} \tag{29}$$

$$\text{where} \quad \eta = \frac{\sum_{j=1}^{M} x_j \, p_j}{\sum_{j=1}^{M} p_j}$$

and M = number of histogram bins. This is similar to (17) using (14) as the MSE.

In theory, equations (28) and (29) are of the same form as (16) and should give similar results. The fundamental difference between them is that (29) uses the histogram of the expected coder input (p_j) where (28) uses the actual input signal. For the case of a uniform or gamma quantizer, p_j will be the histogram of an analytically generated input, not an actual speech signal. In our tests, we have set the variance of all analytically generated histograms equal to the variance computed from the corresponding coder input speech file, hence the second term in (29) representing variance is equivalent to the numerator term in (28). However, the MSE term in (29) is computed relative to the histogram rather than relative to the coder input signal as in (28). The data points used in Figures 14 and 15 result from computations in which the parameters NBIN = 4096 and CTST = 0.5. The signal variance values used by OPT1 in the calculation of SNR_Q as plotted in Figure 15 were obtained from SPCHSTAT and were computed in a manner similar to equation (29), from a histogram speech file. For comparison, program STAT1 was written to compute signal variance as shown in equation (32). The results of both these computations appear in Appendix Tables A8 and A9. For any of the six sentences, the σ_x^2 values computed by the two methods differed by less than 0.12 % and the standard deviations by less than 0.06 %. This result indicates that differences in Figure 14 and 15 results are due primarily to the method the MSE term was calculated, and not the σ_x values used.

The general trend in Figures 14 and 15 indicate an approximate 6 dB per bit increase in the SNR for both uniform and gamma quantizers. The gamma curves decrease in slope as the number of quantization levels increase beyond 64 levels. Eventually the gamma quantizer results in lower SNR measurements than the corresponding uniform quantizer. This convergence can be explained by observing the spacing of decision and reconstruction levels within the quantizers with respect to the histogram bin width. For a 256 level uniform quantizer and a 4096 bin histogram, each decision level is separated from the next by a distance equal to sixteen histogram bin widths. For a 256 level gamma quantizer the decision levels will be spaced approximately one-half of a histogram bin width apart near the zero level. For closely spaced decision and reconstruction levels, errors in the linear approximation of bin counts, equation (12), in the region of rapidly changing histogram slope cause errors in the placement of the levels. A solution to this problem would involve either an increase in the number of histogram bins, or a change in the interbin interpolation expression to a nonlinear interpolation scheme. Either solution brings with it the problem of an increased computation time, which is not acceptable. Since the SNR_Q values in Figure 15 are inversely proportional to the computed quantizer MSE, we see that the MSE decreased logarithmically with each additional reconstruction level. This relationship is expected from the type of minimization that is being applied. In Figure 14, we see that in quantization of actual speech, the presence of a reconstruction level at zero (mid tread quantizer) increases the SNR_F due to a decrease in idle channel quantization noise. The uniform-odd quantizers exhibit a much greater increase in SNR over uniform-even than does the gamma-odd over gamma-even quantizers. Since a gamma quantizer has levels spaced much closer together near zero than a corresponding uniform quantizer, less difference is expected between gamma-even and gamma-odd quantizers. The gamma-even and gamma-odd curves converge for quantizers of greater than eight levels. For all quantizers based upon analytical histograms, solutions using the floating zero option exhibited a smaller MSE than the corresponding fixed zero solution. This difference is primarily due to the change of the natural gradient of the MSE minimization caused by the forced zero constraint. Thus, for a given number of iterations, the floating zero option results in a smaller quantizer MSE than the fixed zero option. Tables of the data in Figures 14 and 15 appear in the Appendix as Tables A10 and A11.

Figures 16 and 17 illustrate changes in SNR_F as a function of number of histogram bins (NBIN) for several different quantizers. The SNR value plotted on the graphs is the result occurring at CTST = 0.01 or NIT = 1000, which ever is met first, thus no further minimization for any NBIN and NLOUT combination was expected. Figure 16 presents the SNR_F of PCM coded sentence S1, hence no inference of the MSE can be directly made. Figure 17 presents the SNR_Q computed from MSE results of the quantizer calculations. From Figure 17 we can see that for a quantizer of greater number of quantization levels, an increase in the number of histogram bins is required to obtain the full benefit of MSE minimization. Table 7 presents a suggested minimum number of histogram bins for a specified number of quantizer output levels. The plots for gamma distributed quantizers and uniform distributed quantizers are very similar with respect to the number of bins at which each locus approaches its maximum SNR value. This similarity suggests that there is little dependence upon histogram shape, implying that the results of Table 7 will also be valid for speech histograms. A six dB per bit increase in SNR for uniform quantization can be easily seen in both Figures 16 and 17. The SNR gain per bit for gamma quantizers can be seen to decrease at the higher NLOUT numbers as was also noted in

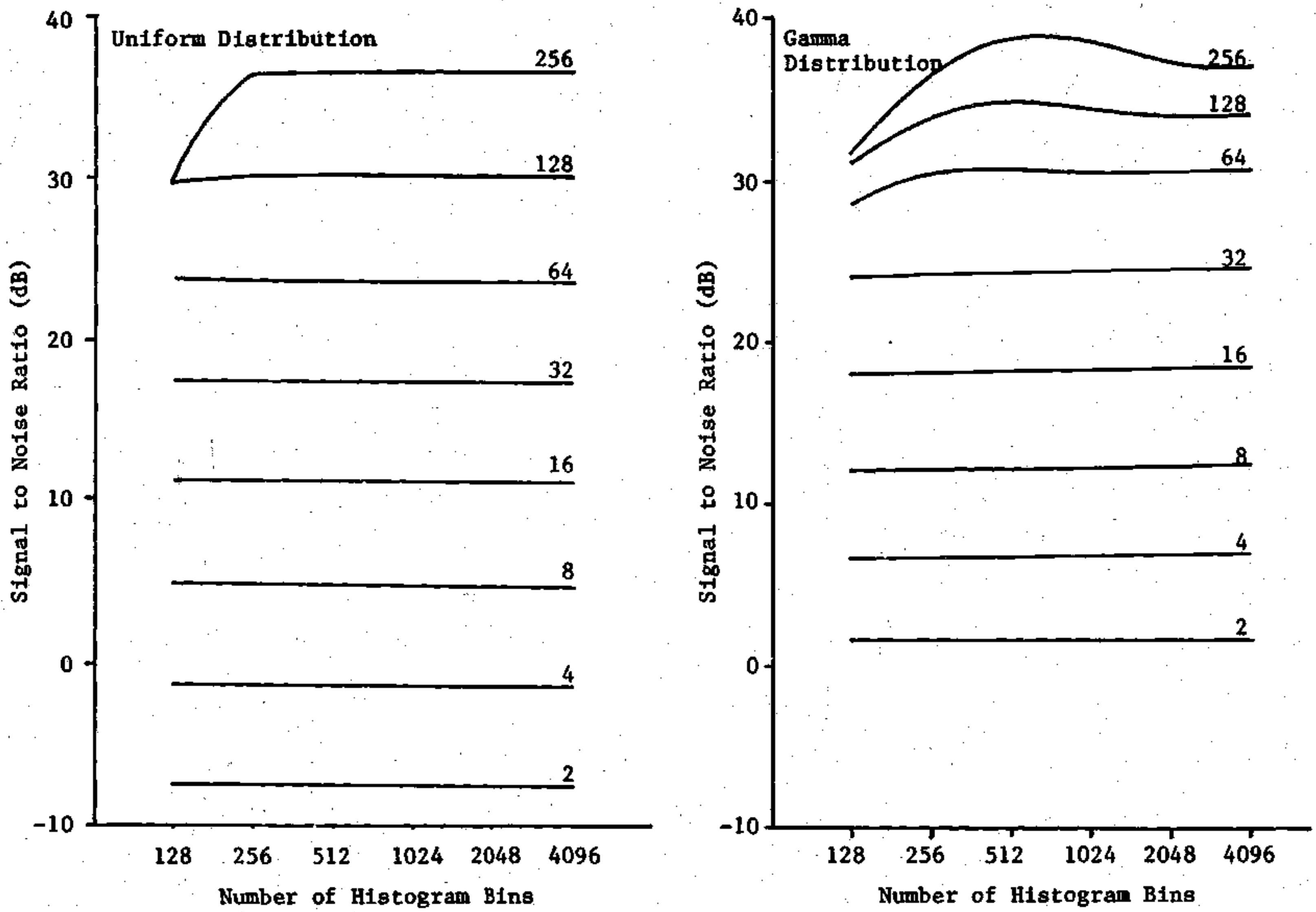


Figure 16. Signal to Noise Ratio Computed from Uniform and Gamma Distributed Quantizers

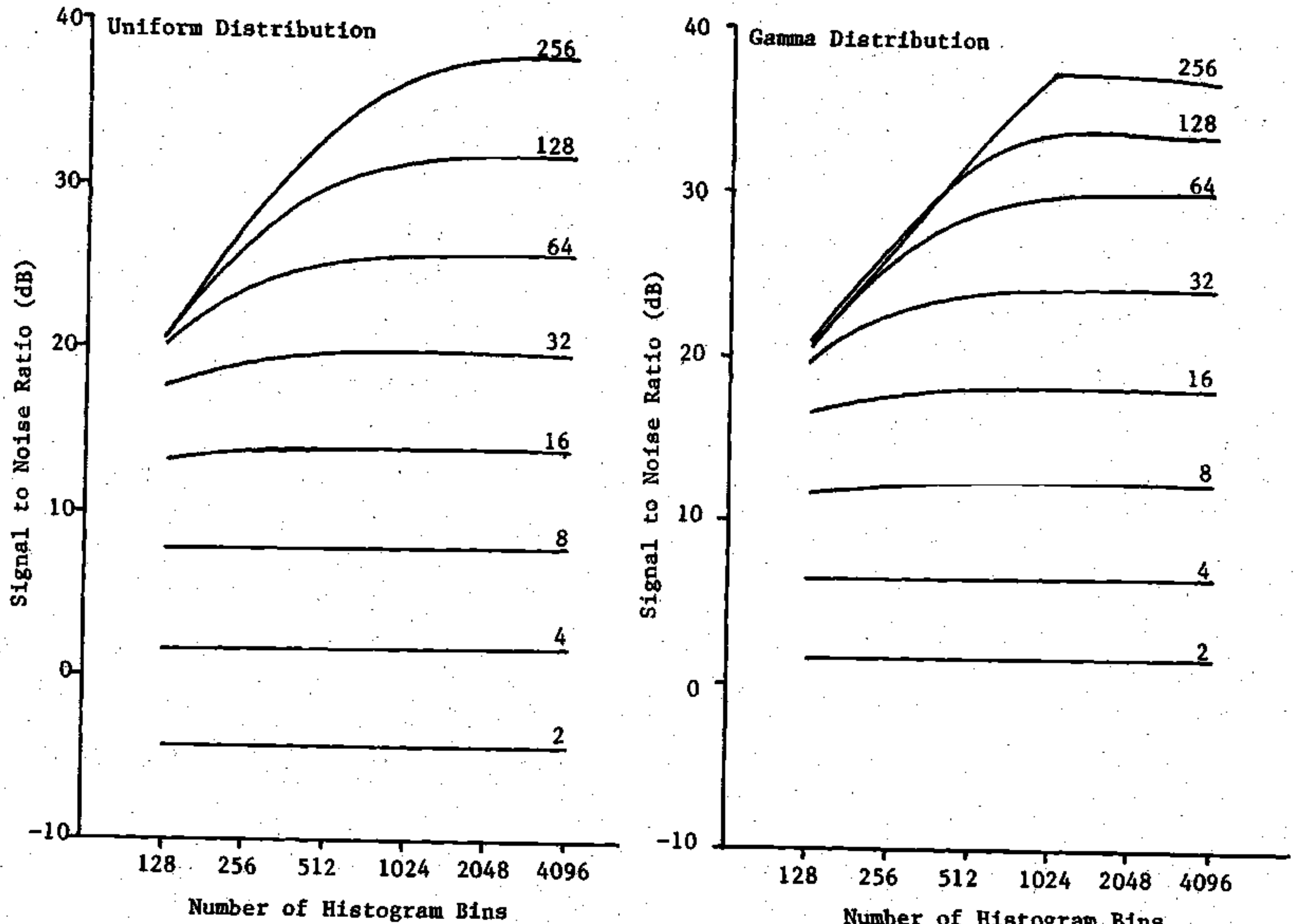


Figure 17. Signal to Noise Ratio Computed from Uniform and Gamma Distributed Quantizer MSE

Table 7. Choice of NBIN for a Specified Number of Quantizer Output Levels

NLOUT	Minimum NBIN	$\frac{NBIN}{NLOUT}$
2	128	64
4	128	32
8	512	64
16	1024	64
32	1024	32
64	2048	32
128	2048	16
256	4096	16

Figures 14 and 15. Figure 17 presents the most useful results of this pair of graphs since it indirectly shows how the quantizer MSE is effected by choice of NBIN and NLOUT.

Computation Time Estimate

Through careful choice of NBIN and CTST we wish to minimize the quantizer calculation time while maintaining an adequate amount of MSE minimization. For each quantizer calculated in the Parameter Study, NIT and TIME (time to perform steps IV, V and VI of Figure 7, NIT times) were recorded. The TIME data was declared unusable since, on a multi-ground computing system in which central processor use is timeshared between two users, we have little confidence that the measured times include only OPT1 operations. To supplement this loss of data and provide a more illustrative body of information, an estimate of the computation time has been made. The derivation of these estimates is presented in Appendix D. No effort was made to tailor these estimates to any particular computing machine, however the manner in which the derivation is presented should allow one to insert specific operation times and arrive at a realistic timing estimate. For the current study we have divided all FORTRAN program instructions into two classes. Memory reference instructions in which two words are either compared or combined constitute the first class. Operations of this class are assigned 10 time units, or 10 μsec. The second class includes all other operations of a less complex nature including sign changes, equivalences and jumps. Operations of this class are assigned 4 time units or 4 μsec. No effort was made to differentiate between real and integer operations. Two timing expressions are given as a result of the foregoing approximations. The first expression estimates TIM, the time required for one iteration of the algoritm. This corresponds to computing steps IV, V, and VI of Figure 7, and is given as

$$\text{TIM} = 564(\text{NLOUT}) + 72(\text{NBIN}) - 48 \quad \mu\text{sec.} \tag{30}$$

The second expression estimates the time required to calculate a quantizer and perform the quantization as is done in program OPT1. This corresponds to computing steps I through IX of Figure 7 and is given as

$$\text{TIME} = 85(\text{NLOUT}) + 232(\text{NBIN}) + 164(\text{M}) + 296 + \text{NIT}(\text{TIM})$$

For all the speech files considered in this study, each representing approximately three seconds of speech, M = 24576, thus

$$\text{TIME} = 85(\text{NLOUT}) + 232(\text{NBIN}) + 4030760 + \text{NIT}(\text{TIM}) \ \mu\text{ sec.} \tag{31}$$

The term containing M represents the sum of the time required to calculate a histogram of the input speech file and time required to code the input file using the computed optimum quantizer. This time is approximately 4.0 seconds and represents an overhead to all timing calculations which could, in a real-time block-quantizing implementation, be divided into separate parts of a pipeline.

Figures 18, 19 and 20 illustrate the timing estimates applied to a 4-level quantizer. Figures 18 and 19 differ in only two important

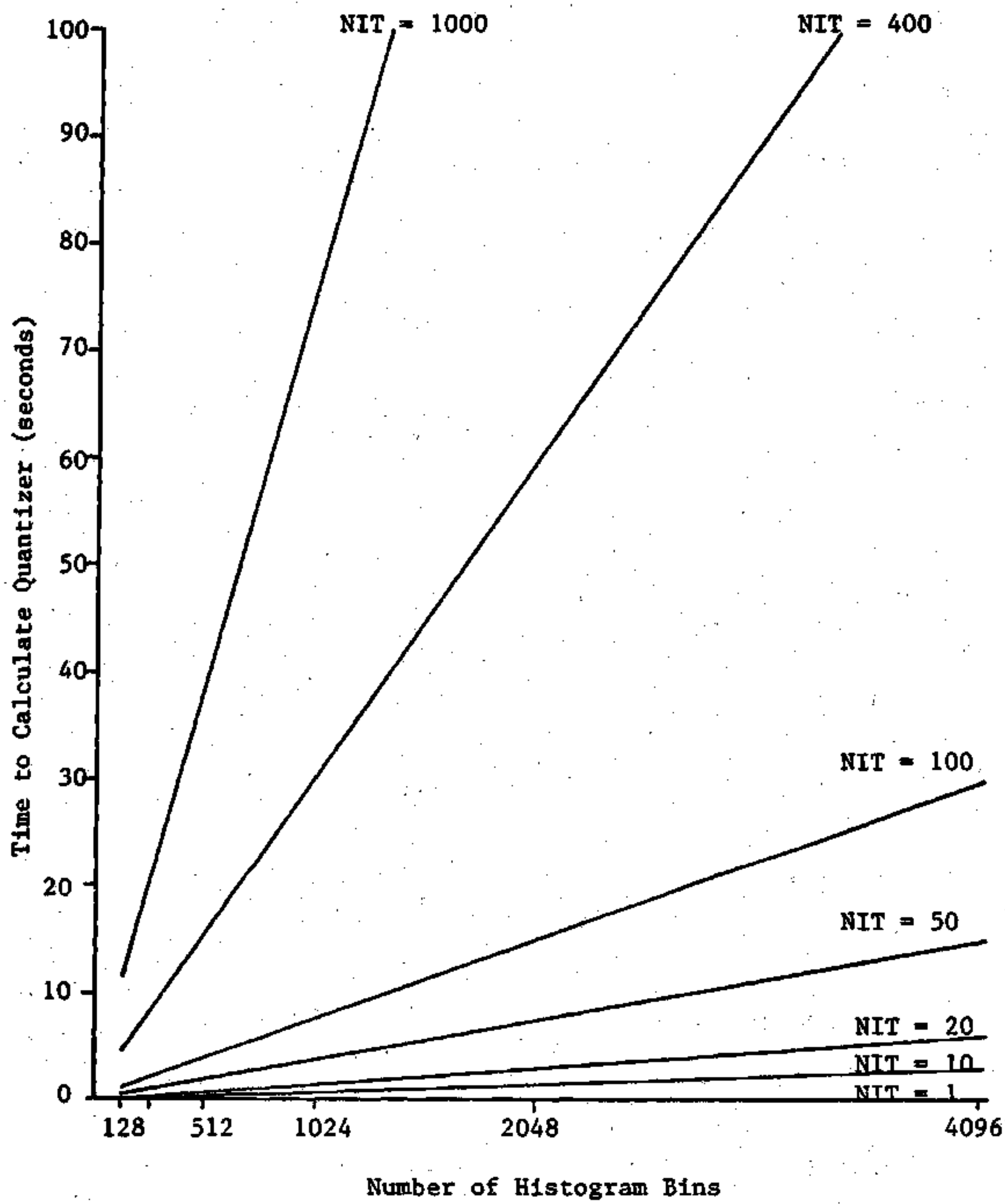


Figure 18. Time to Calculate a 4-Level Quantizer

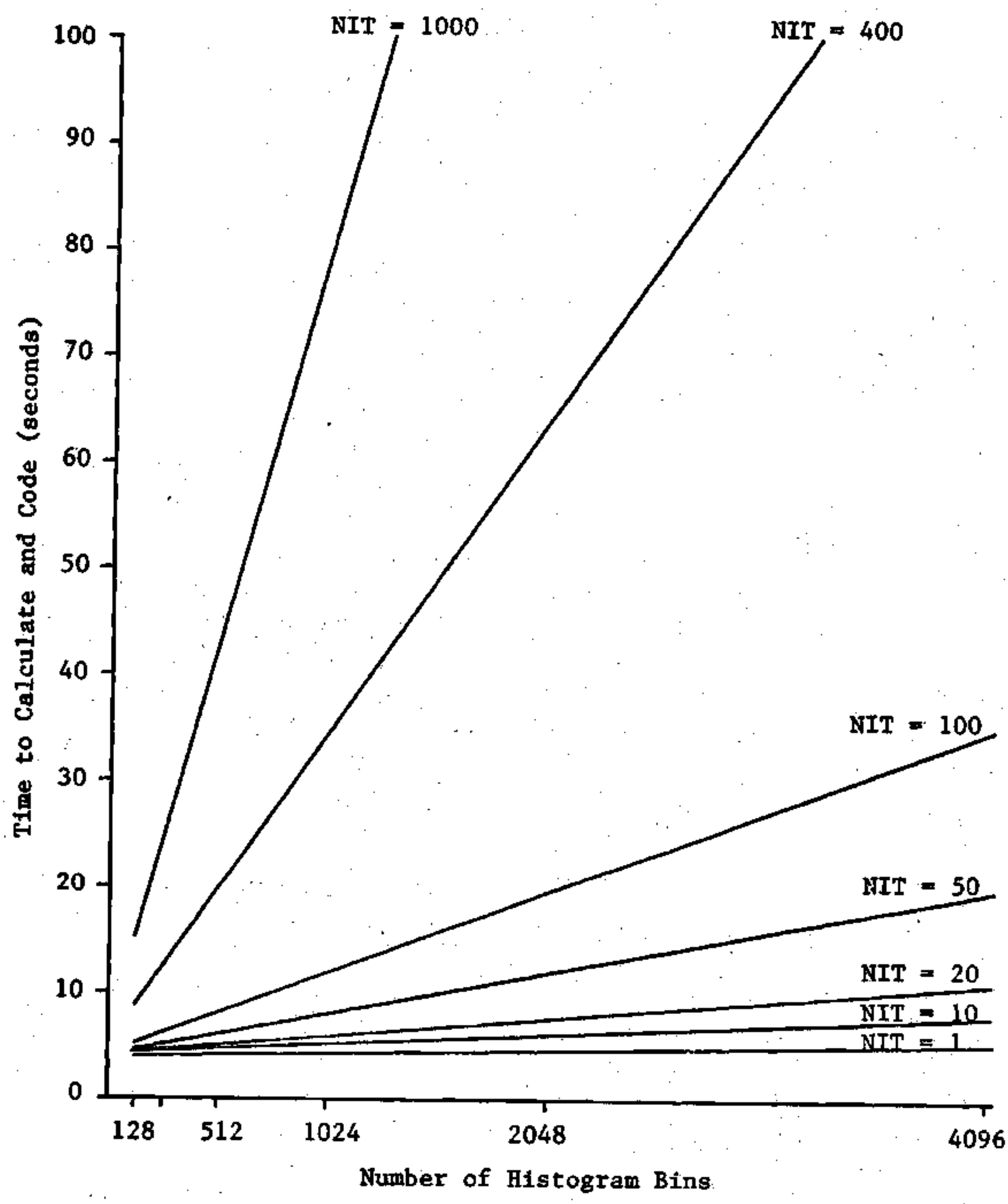


Figure 19. Time to Calculate a 4-Level Quantizer and Code One Speech File

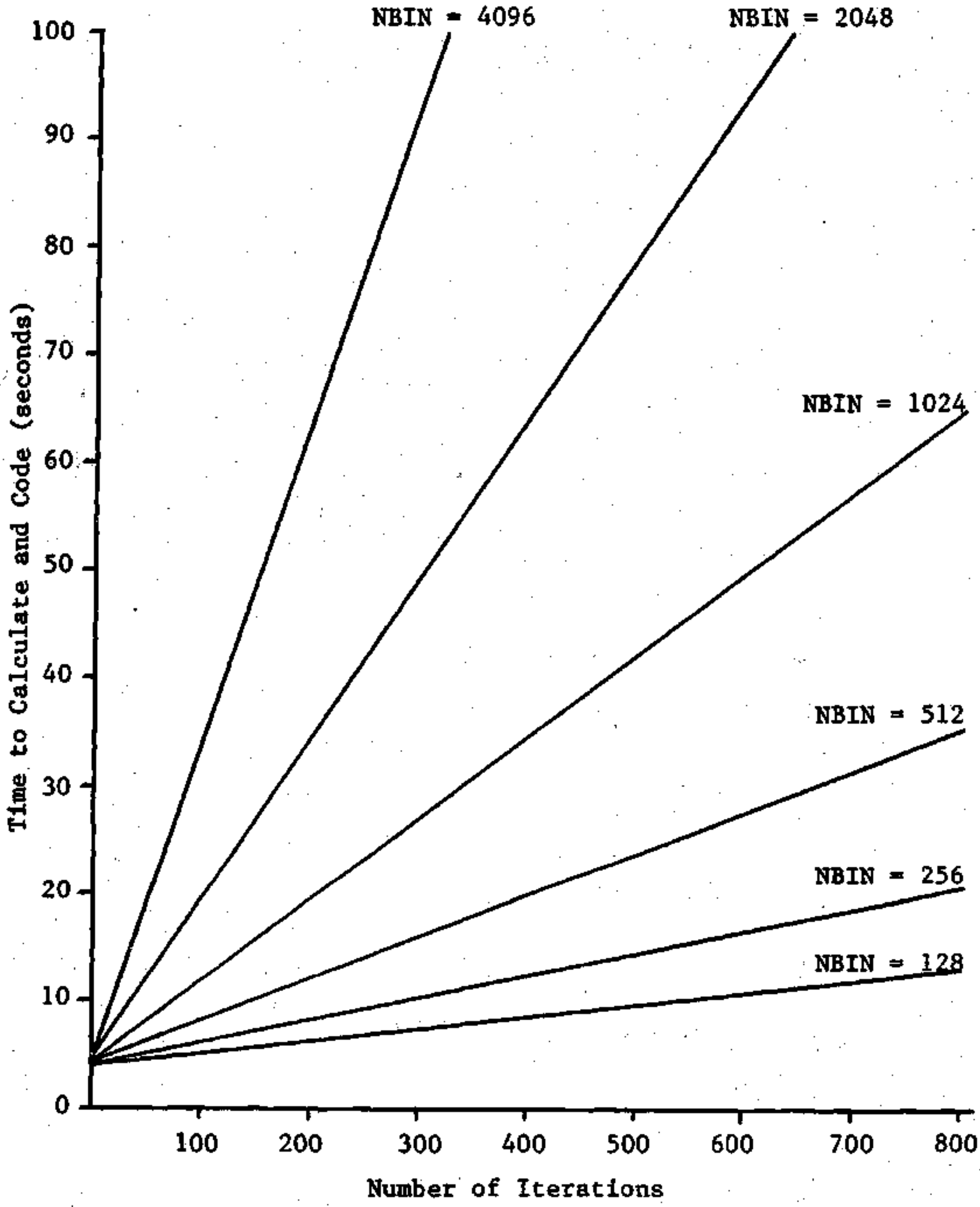


Figure 20. Time to Calculate a 4-Level Quantizer and Code One Speech File as a Function of Number of Algorithm Iterations for Several Histogram Sizes

ways. First every point in Figure 19 has added to it the 4.0 seconds time as described earlier. This time need not be considered quantizer calculation time in a practical implementation of the coder. Second there is a slight increase in the slope of each locus due to the 232(NBIN) term of (31). From these first two figures it is easy to see the dramatic increase in quantizer calculation TIME as number of iterations increase. The points in Figure 19 are re-plotted in Figure 20 in a different format. From this illustration we see the less dramatic increase in time as the number of quantizer bins increase.

From timing trends illustrated by Figures 18, 19 and 20 the first three basic rules governing parameter choice may be stated in order of decreasing importance.

1) Keep the number of iterations to a minimum.

2) Keep the number of histogram bins as low as possible.

3) Keep the number of output levels low.

The final statement concerning number of output levels is of little real value since that parameter is not usually free to be chosen. Also the magnitude of NLOUT has only a small effect on the algorithm computation time. From these graphs, we can conclude that NLOUT sets the base value of each calculation (time required for NIT iterations on a 128 bin histogram), but the slope of the timing curve is set by NIT and NBIN. From (30) and (31) we see that any term with NBIN in it will swamp contributions from the NLOUT terms if the NBIN choices suggested by Table 7 are made.

Based upon the results of the Convergence tests and Parameter Study, a set of rules for choosing NBIN and CTST may now be stated along with an indication of the expected results. Equations (27) provide information for choosing CTST based upon the desired MSE minimization. CTST should be as large as possible in order to keep the number of algorithm iterations to a minimum. Table 7 should be consulted next to determine the value of NBIN. The quantizer MSE will fall off significantly for quantizers of greater than 16 levels if NBIN is set less than the suggested value. A larger NBIN value will only result in more computation time with no useful gain in SNR. Table 8 has been compiled to illustrate the results of these suggested parameter choices using estimated iteration times. The actual times are presented to show that our estimates are at least order of magnitude correct. It should be pointed out that quantizers computed with the zero level fixed to zero, will converge to the CTST limit in approximately one half the number of iterations required for floating zero computed quantizers. These combined results suggest that it should be possible to employ this algorithm in locally-optimum speech coders using coders of 4 or less bits, and blocks of greater than one second in length. Use of a 5-bit quantizer may be possible in a dedicated hardware implementation.

Table 8. Number of Iterations and Estimated Calculation Time for Gamma Float Quantizers at CTST = 0.5

NLOUT	NIT	Calculated TIME	Measured TIME
2	23	4.30	0.0
4	52	4.65	0.0
8	90	7.87	35.0
16	216	22.13	74.0
32	618	60.96	216.0
64	>1000	188.02	284.0
128	>1000	224.12	343.0
256	>1000	444.25	678.0

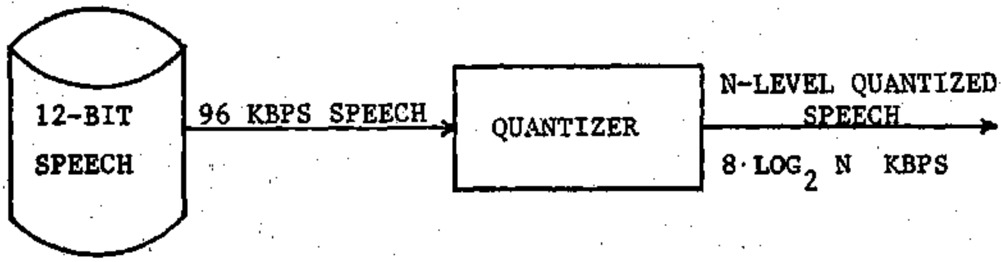
CHAPTER V

PCM AND ADPCM CODER SIMULATION RESULTS

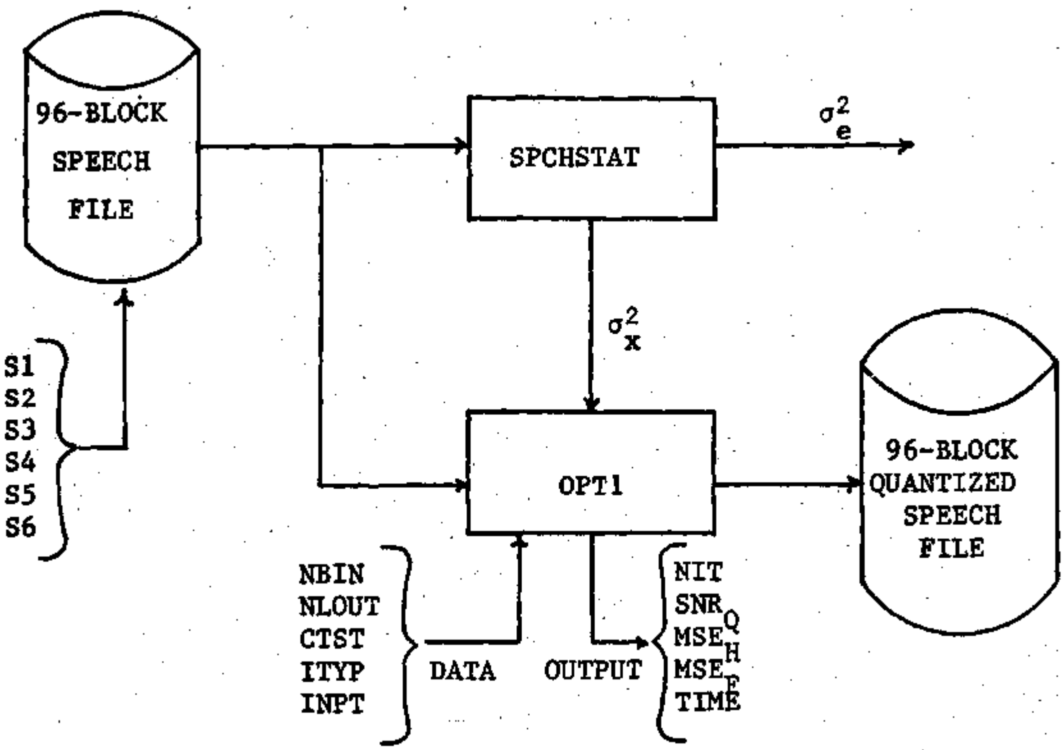
PCM Coder Implementation and Results

The PCM speech coder was implemented by program OPT1. Figure 21 is used to illustrate relationships between input and output files and programs. To obtain a PCM coded output speech file, one of the six input speech files was input first to program SPCHSTAT from which an estimate for the variance, σ_x^2, of the file was obtained. Estimates of energy, maximum and minimum amplitudes were also made by SPCHSTAT, but not required by OPT1. Next, the speech file, variance, and OPT1 parameters were input to OPT1, and a set of quantizer decision and reconstruction levels was computed as shown by steps I through VI of Figure 7. The parameters NBIN, NLOUT and CTST have been explained earlier. ITYP is the mnemonic for a number used to select histogram (and quantizer distribution) type. INPT is the mnemonic for a number that selects either the fixed or floating zero option. After computing the quantizer, the speech file was quantized and the coded samples written into an output file. For each speech file that was coded, SNR_Q from equation (16), MSE from equations (14) and (17), number of iterations (NIT) and computation TIME were output and recorded.

Each of the six sentences were coded with quantizers of uniform, Laplacian, gamma and speech distributed histograms. The analytical histograms were computed with the variance, σ_x^2 equal to the variance of



a) Block Diagram



b) Program Flow Diagram

Figure 21. PCM Speech Coder Simulation Flow Diagram

the speech file that was to be coded. No effort was made to limit the abscissa range to that of the speech file, thus all histograms have count bins uniformly spaced for all amplitudes between -32768 and +32767. From equations (7) and (8), repeated here for reference

$$y_k = \frac{\sum_{j=i_{k-1}}^{i_k} x_j' \, p_j}{\sum_{j=i_{k-1}}^{i_k} p_j} \qquad \text{for } k = 1,2,\ldots,N$$

$$x_k = (y_k + y_{k+1})/2$$

we can see that the assignment of the decision level endpoints x_0 and x_N has no effect upon the location of the other N-1 decision levels or N reconstruction levels. This statement is true as long as x_0 is less than or equal to the most negative non-zero count histogram bin edge and x_N is greater than or equal to the most positive non-zero count histogram bin edge. Thus, for the speech histogram quantizer, no degradation in quantizer performance is caused by the assignment of decision level endpoints at the limits of the possible histogram range. The OPT1 program parameters used for the PCM simulations are given below as

1) NBIN = 4096

2) CTST = 0.05

3) NLOUT = 3,4,7,8,15,16,31,32,63,64

From the number of NLOUT parameters and the fact that six sentences are coded each using four different quantizer distributions, we see that a total of 240 different coded speech files were obtained as a result of the simulations. For quantizers employing uniform, Laplacian and gamma histograms, the fixed zero option was used in OPT1. This insured the greatest amount of symmetry in the resulting quantizer characteristics, with a zero reconstruction level for quantizers with NLOUT = 3,7,15,31 and 63. For quantizers from speech-distributed histograms, OPT1 employed the float zero option to allow for the greatest amount of MSE minimization. From data taken in the OPT1 Parameter Study, we note that negligible difference is expected between quantizers computed with either the fixed or floating zero option enabled.

An estimate was made of the expected results from uniform PCM coding of sentences S1 through S6. Recall that SNR of a uniform quantizer [9] can be expressed as

$$\mathrm{SNR(dB)} = 10\ \mathrm{Log}_{10}\left\{\frac{\sigma_x^2}{\sigma_x^2}\right\} = 6B + 4.77 - 20\ \mathrm{Log}_{10}\left\{\frac{x_m}{\sigma_x}\right\} \quad (32)$$

where B is the number of bits representing the quantized output and x_m is the maximum possible input amplitude. Table 9 was computed from this expression with appropriate values of σ_x inserted. These table entries represent the maximum possible SNR from a uniformly distributed quantizer. Similar expressions for SNR of Laplacian and gamma quantizers were not developed. A comparison of Table 9 results with the

Table 9. Theoretical PCM Coder Results with a Uniform Quantizer

File Name	Number of Quantizer Levels 4	8	16	32	64
S1	1.65	7.65	13.65	19.65	25.65
S2	-3.82	2.18	8.18	14.18	20.18
S3	0.92	6.92	12.92	18.92	24.92
S4	1.06	7.06	13.06	19.06	25.06
S5	0.12	6.12	12.12	18.12	24.12
S6	-1.40	4.60	10.60	16.60	22.60

rankings of Table 3 of Chapter III indicate that the sentence with the greatest energy (and variance) is expected to have the greatest uniform SNR, with expected SNR decreasing as the energy of the sentence decreases.

Of the data recorded in the simulations, SNR_F computed by equation (16) is the most useful. The MSE_F calculation from (17) gives us no new information on quantizer performance and the MSE_H from (14) is not based upon the actual coded speech. The TIME data is not used due to its inaccuracies as explained in the Parameter Study section.

Appendix Tables A12, A13, A14 and A15 list the SNR and MSE results for each of the 240 coded speech files. Figure 22 is a graph of the maximum and minimum SNR_F at each number of output levels for uniform and speech-histogram (optimum) quantized speech. The most striking feature is the uniform curve which exhibits a significantly greater SNR for quantizers of $2^B - 1$ levels than for quantizers with 2^B levels. Here, B is the number of bits representing each coded output sample. The optimum quantizer results do not exhibit this phenomenon, as SNR linearly increases with the logarithm of the number of quantization levels. In the OPT1 Parameter Study discussion of Chapter IV we suggested that the smoothing of the SNR versus NLOUT curves for quantizers of distributions different from uniform, is due to the ability of the quantizer to assign a near-zero quantization level to input samples of very small amplitude, thus reducing the idle channel quantization noise. Figure 14 of Chapter IV can be compared with Figure 22. We see that the SNR of the optimum quantizer does not increase as much from 32 to 64 levels as it does between quantizers of fewer levels.

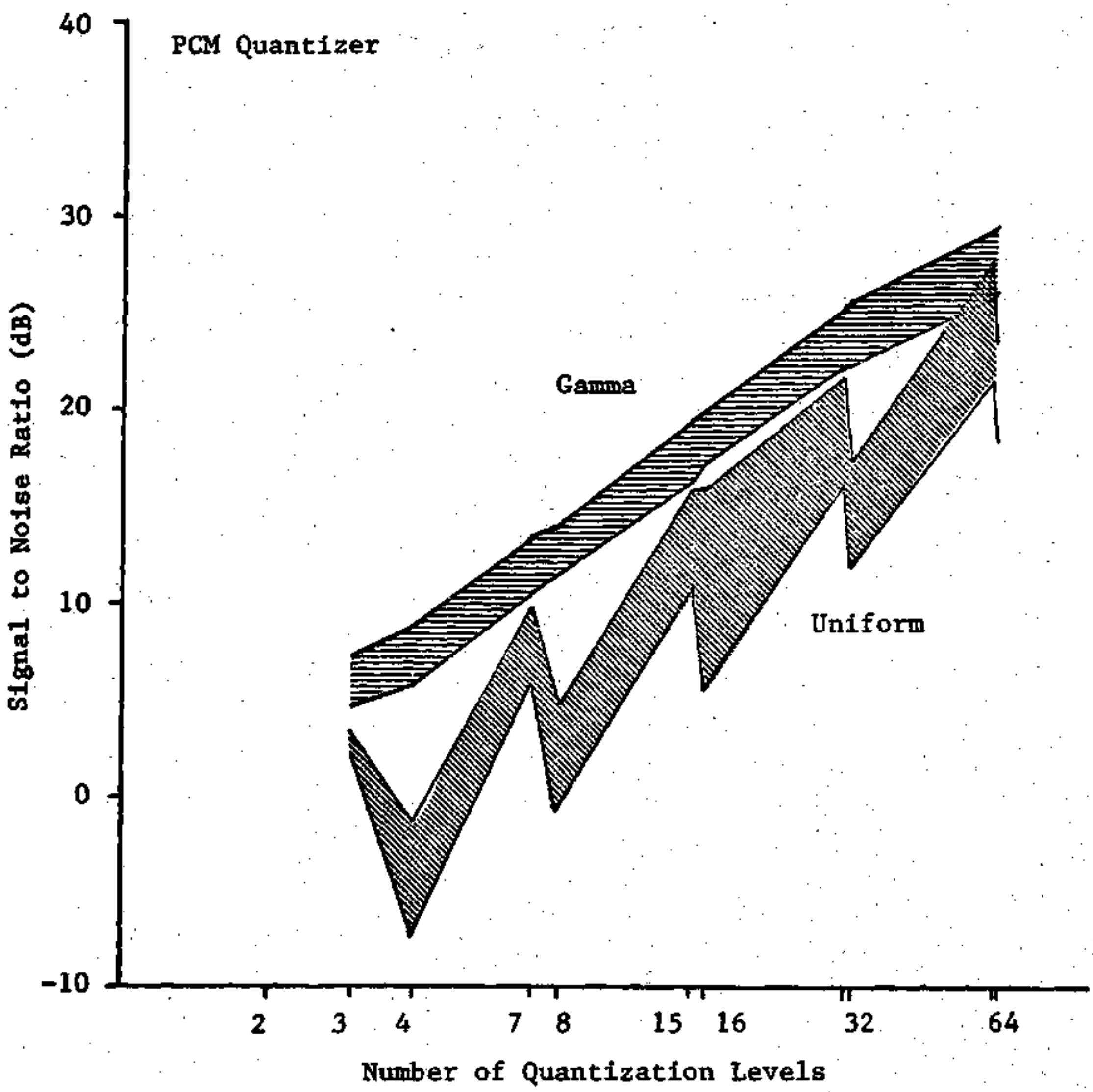


Figure 22. Range of Coder SNR for PCM Coded Speech Files S1 - S6

This is also evident in the gamma quantizer of Figure 14. Table 10 presents a comparison to PCM coder signal to noise ratios from quantizers of uniform, Laplacian and gamma distributions with the SNR from optimum quantizers. The entries in the table represent a difference in decibels between the listed quantizer type and the comparable optimum quantizer SNR result. A negative number implies the quantized speech for the listed quantizer type had a SNR greater than the optimum quantizer of the same number of levels operating upon the same speech file. From a cursory view of the table, one can see that the optimum (speech-histogram) quantizer gives the best performance in the speech coder for NLOUT $\leq$ 32. There is one exception in which a 31-level gamma quantizer is marginally superior in coding sentence S5. For quantizers with a large number of levels, we expect that the Laplacian, gamma and optimum quantizers will give very similar results. This is due jointly to the fact that comparable reconstruction and decision levels near zero may be the same within the accuracy limit of one bit of the input amplitude range, and due to errors in the approximation of the histogram between bins as explained in Chapter II. It is possible that Laplace and gamma distributed quantizers of 63-levels will perform marginally better than the 63-level optimum quantizer due to the assignment of a reconstruction level exactly on zero in the Laplace and gamma quantizers. This premise is supported by the entries in Table 10.

PCM encoding of sentence S2 appears to be much more difficult than the coding of the other five sentences. In Figure 22, the minimum SNR curves are both plotted from S2 SNR results. Table 3 lists S2 as

Table 10. Uniform, Laplacian and Gamma PCM Coder SNR Comparison

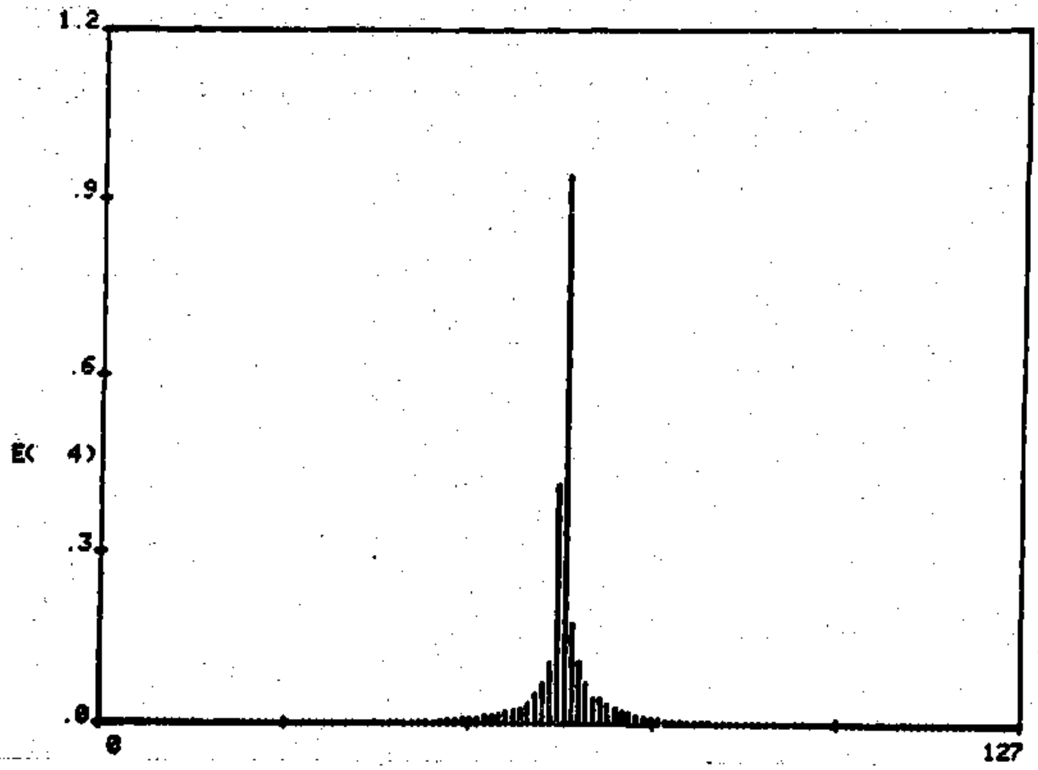
Quantizer Type	NLOUT	Coded Output File S1	S2	S3	S4	S5	S6	Ave.
Uniform	3	4.55	2.84	3.36	3.67	3.28	4.01	3.62
	4	9.69	13.22	9.52	11.02	10.17	12.08	10.95
	7	3.58	4.70	3.91	3.41	4.02	5.04	4.11
	8	9.15	12.17	9.00	9.82	9.72	11.59	10.24
	15	3.55	5.21	4.32	3.07	4.08	4.90	4.19
	16	8.76	11.64	8.67	9.17	9.38	10.99	9.77
	31	3.41	5.98	4.27	3.23	3.99	4.78	4.28
	32	8.14	10.24	7.85	8.18	8.56	9.75	8.79
	63	0.47	3.97	3.14	1.84	2.32	3.31	2.51
	64	4.51	7.85	5.93	6.12	5.64	7.38	6.24
AVE(3→32)		6.35	8.25	6.36	6.45	6.65	7.89	6.99
AVE(3→64)		5.58	7.78	6.00	5.95	6.11	7.38	6.47
Laplace	3	0.71	0.80	0.53	1.20	0.94	1.12	0.88
	4	1.86	1.47	1.67	2.84	1.64	2.10	1.93
	7	0.60	2.49	0.49	1.10	1.86	2.15	1.45
	8	2.05	3.30	1.62	3.38	2.55	3.10	2.50
	15	0.72	4.46	0.41	0.61	1.36	2.37	1.66
	16	2.19	5.52	1.64	2.35	2.65	3.15	2.92
	31	0.44	7.06	0.58	0.24	0.42	1.90	1.77
	32	1.82	7.19	1.44	1.54	1.85	2.50	2.72
	63	−2.41	8.54	−0.72	−1.02	−1.11	1.20	0.75
	64	−1.78	8.90	−0.18	−0.24	−0.65	1.45	1.25
AVE(3→32)		1.30	4.04	1.05	1.53	1.66	2.30	1.98
AVE(3→64)		0.62	4.97	0.75	1.10	1.15	2.10	1.78
GAMMA	3	0.21	0.32	0.04	0.40	0.37	0.51	0.31
	4	1.28	0.77	0.75	1.83	0.89	1.25	1.13
	7	0.78	1.08	0.12	0.57	0.68	0.92	0.69
	8	1.52	1.68	0.84	1.28	1.04	1.40	1.29
	15	0.81	1.66	0.67	0.15	0.13	0.54	0.66
	16	1.31	2.59	1.19	1.00	0.97	0.95	1.34
	31	0.46	3.01	0.44	0.04	−0.30	0.11	0.63
	32	0.83	3.01	0.70	0.38	0.57	0.26	0.96
	63	−2.60	3.17	−0.97	−1.71	−1.91	−1.83	−0.98
	64	−2.59	4.04	−0.85	−1.28	−1.88	−1.82	−0.73
AVE(3→32)		0.90	1.77	0.59	0.71	0.54	0.74	0.88
AVE(3→64)		0.20	2.13	0.29	0.27	0.06	0.23	0.53

the speech file with the lowest variance and energy estimates of the six sentences. From Table 1, we see that S2 contains fewer fricative phonemes than any of the other sentences. A selected group of the simulations using S2 were repeated to recheck our procedure. No procedural errors were detected, therefore we are confident that the results are not in error. The theoretical uniform quantizer results of Table 9 were found to be, on the average, 2.0 dB greater than the actual SNR values from the simulations results. Equation (32), based upon the variance of the speech file, predicted the uniform quantizer results of S2 as accurately as it did for the other five sentences. No other effort was made to determine why S2 gave such radically different results. Figure 23 illustrates histograms of 128 bins derived from sentences S1 and S2.

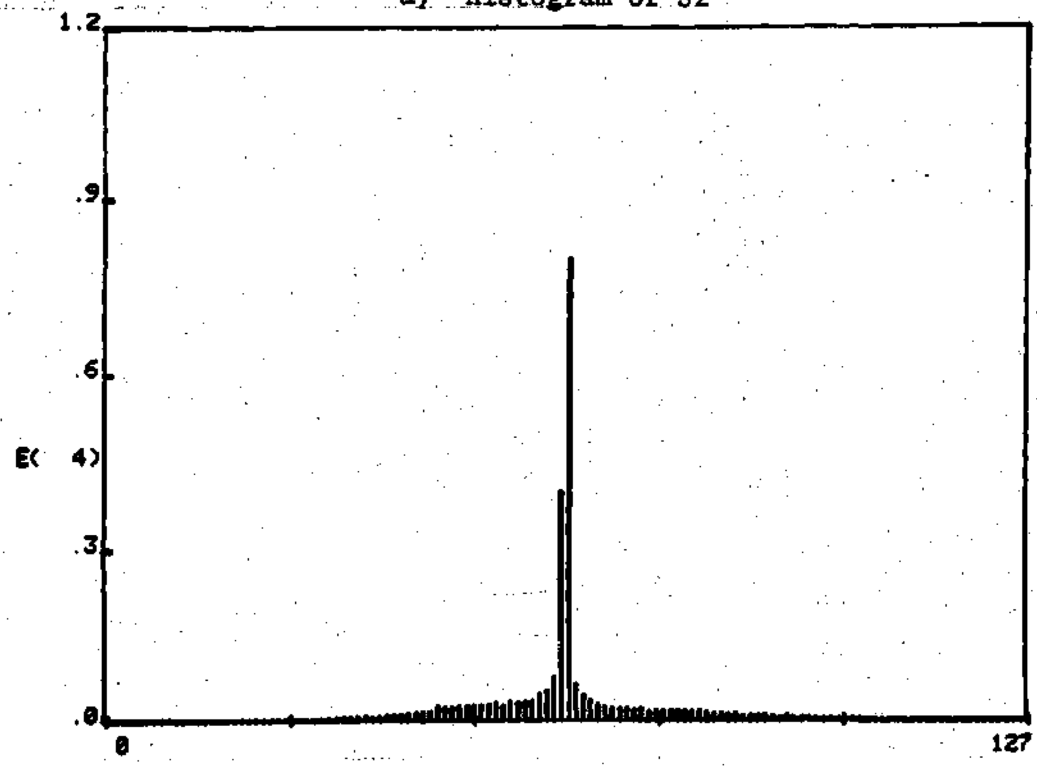
A tabulation of number of iterations, NIT is given in Table 11 for uniform, Laplacian, gamma and optimum quantizers. The MIN, MAX and AVE entries are computed from all six sentences. From the table, we can see that quantizers of 8, 16, 32 and 64 levels can be computed more rapidly from the speech histogram than from the Laplacian or gamma histograms. NIT was limited to be less than or equal to 1000 iterations. Also, CTST = 0.05 was used in these simulations, which result in many more iterations than is necessary for quantizer calculation. The results in this table support the NIT estimate given in the Convergence Test section of Chapter IV.

ADPCM Coder Implementation and Results

A more complex application of the optimum quantizer is in an



a) Histogram of S2



b) Histogram of S1

Figure 23. Histograms of Speech Files S1 and S2

Table 11. Number of Iterations to Optimum PCM Quantizer

Histogram Type		Number of Iterations 4	8	16	32	64
Uniform	MAX	10	31	90	226	564
	MIN	10	31	90	226	564
	AVE	10	31	90	226	564
Laplacian	MAX	24	79	252	810	1000
	MIN	22	75	237	760	1000
	AVE	23	78	247	781	1000
GAMMA	MAX	24	79	247	769	1000
	MIN	23	75	239	1000	1000
	AVE	24	77	243	829	1000
Optimum	MAX	56	89	206	417	1000
	MIN	25	60	121	335	746
	AVE	39	74	162	382	955

ADPCM speech coder as illustrated in Figure 24. The program ADPCOD was written to simulate the operation of this coder. The optimum quantizer is designed to minimize the MSE of the difference signal d(n) rather than the MSE of the input speech, as in the PCM coder. Due to filtering in the predictor loop, the signal d(n) exhibits different spectral characteristics from the speech input, x(n). A linear predictor can be expressed as the weighted sum of previous input samples, or

$$\tilde{x}(n) = \sum_{k=1}^{r} \alpha_k \hat{x}(n-k) \tag{33}$$

where r is the number of predictor coefficients and α_k is the k^{th} coefficient. Noll [8] presents data suggesting that little improvement in coder SNR is expected using predictors with $r > 2$. In this study, a single tap predictor of a constant coefficient value is used. Also, d(n) is compressed in amplitude due to the effects of the adaptive gain feature of the coder. The energy estimate in the adaptive loop of the coder computes an estimate using the relation

$$a(n) = K \left[\frac{\sum_{k=1}^{f} c(n+k)^2}{f} \right]^{\frac{1}{2}} \tag{34}$$

where f is the number of samples per frame and K is a scaling constant. a(n) is computed at the beginning of each frame, and the value is then

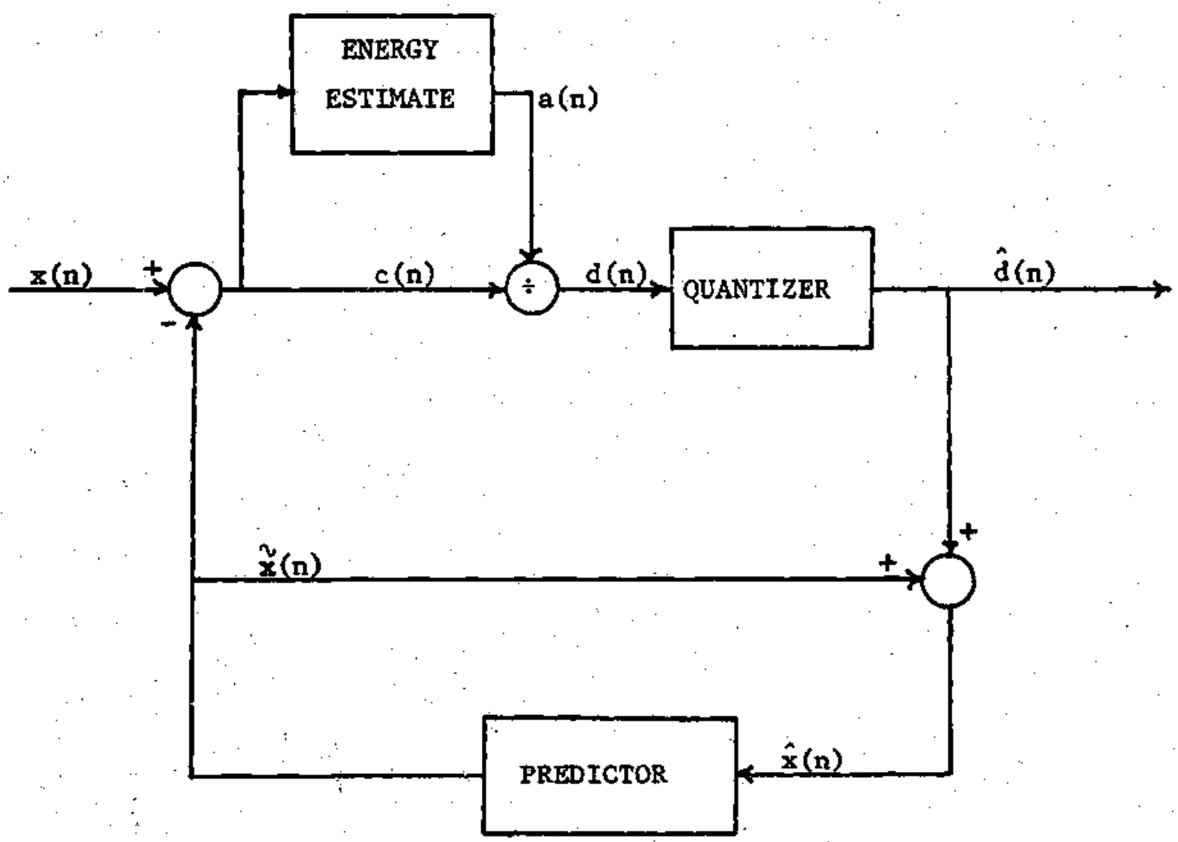


Figure 24. ADPCM Speech Coder Block Diagram

repeated for each sample within that frame. From Barnwell [5], the following parameter values were chosen for use in the simulations;

$$f = 64$$

$$\alpha_1 = 0.86$$

The frame size of 64 samples implies an energy computation every 20 milliseconds of speech. By designing a quantizer to the compressed signal d(n), it was expected that this speech coder yield a significant SNR improvement over the PCM coder. Also, since d(n) is not a speech signal, it was not expected that the Laplacian and gamma quantizers would give results that are as good as those of the optimum quantizer.

The ADPCM speech coder was implemented by a sequence of programs as shown in Figure 25. Each of the six speech files were input to program ADPCOD, the ADPCM speech coder. This initial run through the coder was performed with no quantizer in the coder forward path. A file containing the compressed prediction error, d(n), as shown in Figure 24, was made for each sentence. The error files, labled SE1, SE2, SE3, SE4, SE5 and SE6 were then input to SPCHSTAT for estimation of their statistics. Table 12 gives the statistics of interest for each of the six error files. Three items are worth noting in comparing the statistics from the error files with the statistics of the actual speech file. First, the variance measure of the error files is quite similar for all six sentences as opposed to the widely different variance estimates for the speech files. Second, the energy measures for the error files are quite similar and are lower than most of the energy

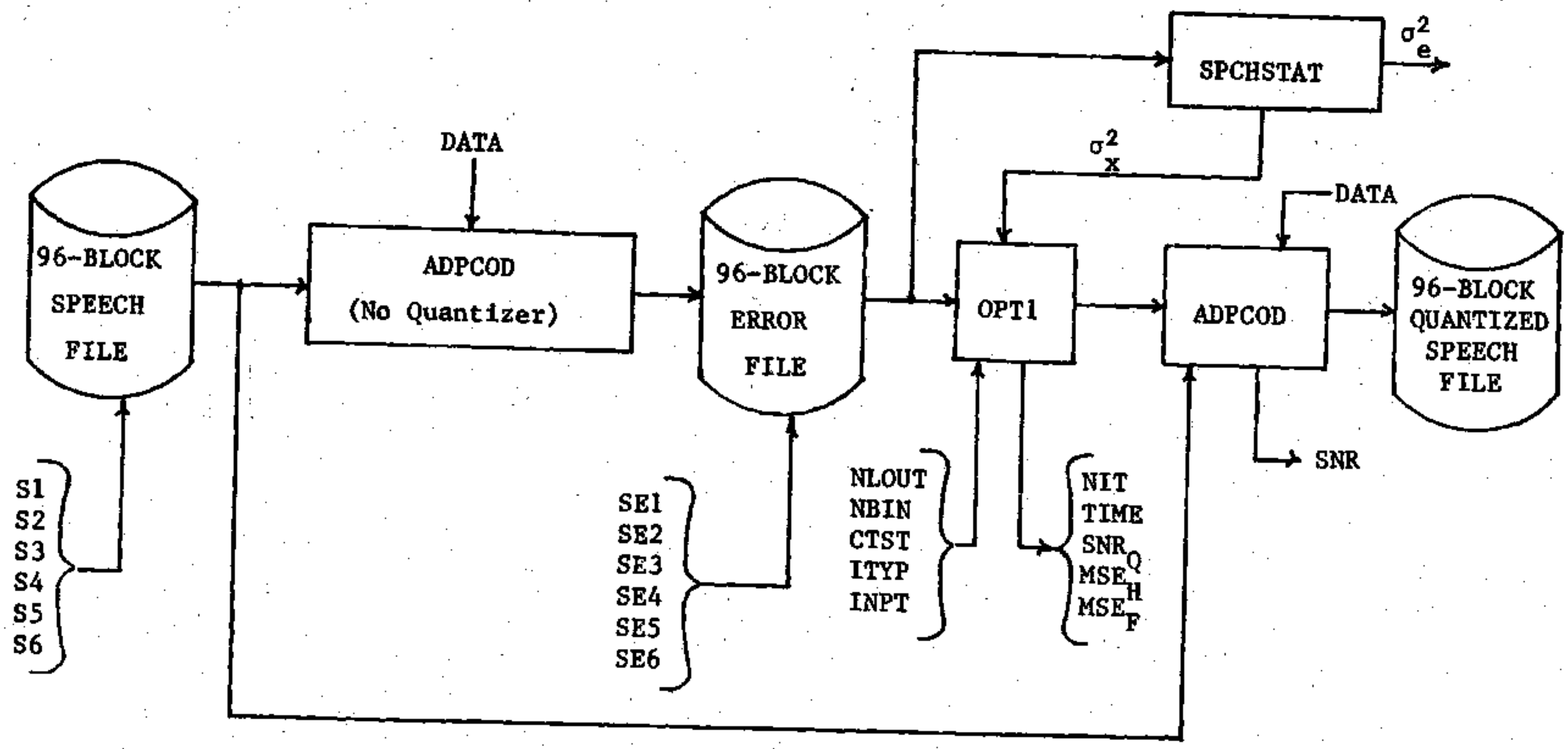


Figure 25. ADPCM Speech Coder Simulation Flow Diagram

Table 12. ADPCM Sentence Error Statistics

Sentence	Mean (η)	Variance (σ_x^2)	Std. Dev. (σ_x)	x_{max}	x_{min}
S1	-5.517	$1.549 \cdot 10^7$	3935	19375	-27743
S2	-2.529	$1.338 \cdot 10^7$	3657	16399	-23503
S3	13.105	$1.551 \cdot 10^7$	3939	17055	-20911
S4	17.603	$1.400 \cdot 10^7$	3742	24079	-19823
S5	-25.604	$1.395 \cdot 10^7$	3735	20463	-21935
S6	-14.078	$1.352 \cdot 10^7$	3677	22975	-21151

measures from the speech files. And third, the range of amplitudes is noticeably smaller in the error files than with the samples in the speech files. Since the error file statistics are quite similar for all six sentences, we would expect the resultant optimum quantizers to also be very similar in construction and performance. After an estimate of the variance is obtained, the error file, σ_x^2 and OPT1 parameters were input to OPT1, and a set of quantizer decision and reconstruction levels was computed in the method shown by steps I through VI of Figure 7. It is important at this point to note that the quantizer characteristic is computed based upon the histogram and statistics of the predictor error signal rather than upon the coder input speech file. Figure 26 illustrates a 128 bin histogram of sentence S2. The OPT1 parameters used to compute ADPCM coder quantizers were exactly the same as those used to compute PCM coder quantizers. Finally, the speech file, quantizer decision and reconstruction levels, and ADPCOD program parameters were input to ADPCOD for the coding of each speech file. The coded output, y(n) from Figure 24 was written into an output file. Signal to noise ratio is computed by ADPCOD from the expression

$$\mathrm{SNR(dB)} = 10 \operatorname{Log}_{10}\left\{\frac{\sum^{M} x^2(n)}{\sum^{M} (\hat{d}(n)-d(n))^2}\right\} \tag{35}$$

and was output for each speech file that was coded. Outputs from OPT1 include $\mathrm{SNR_F}$ from equation (16), MSE from (14) and (17), NIT and

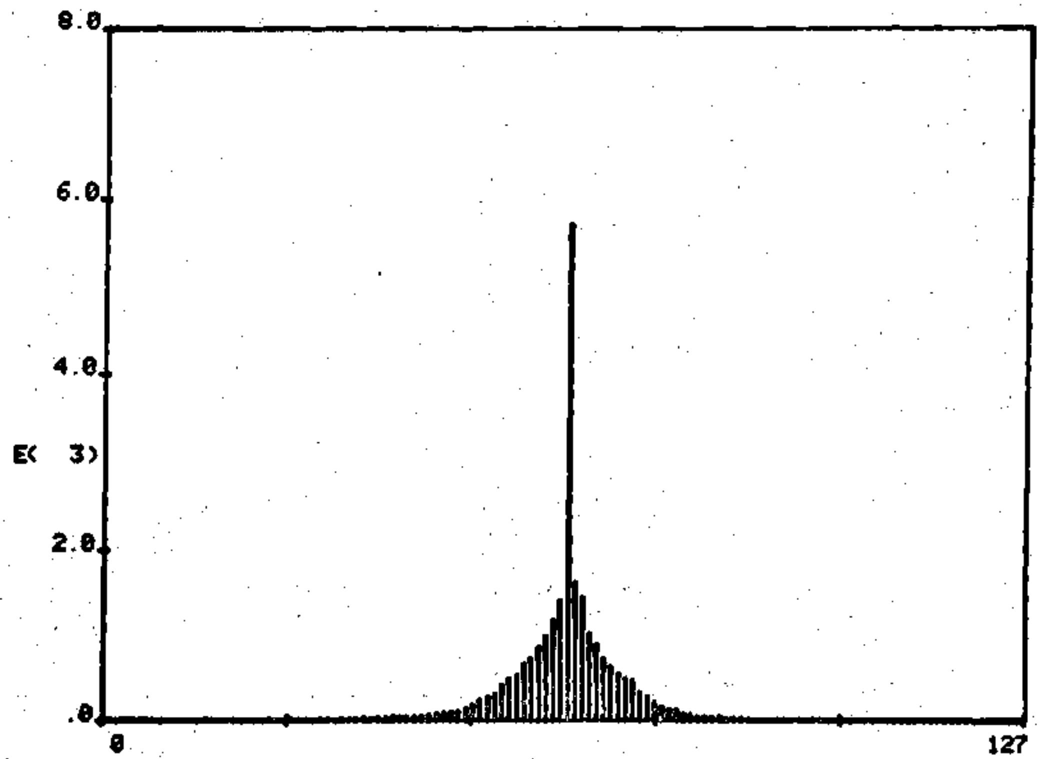


Figure 26. Histogram of ADPCM Coder Error File for Sentence S2

quantizer computation TIME. Of these data, only NIT is useful since the MSE and SNR measures are relative to PCM coding of the error file.

Each of the six sentences were coded with quantizers of uniform, Laplacian, gamma and error file histogram distributions. The analytical histograms were computed with variance equal to the variance of the prediction error file for which the quantizer was designed. With the exception of the variance, histograms were constructed by OPT1 in exactly the same manner as they were in the PCM coder simulations. As for the PCM coder simulations, a total of 240 different speech files were produced by the ADPCM simulations. In computing the quantizers, the fixed zero option of OPT1 was employed for the analytical histograms while the float zero option was used for the error file histograms.

An estimate of the uniformly quantized ADPCM coder signal to noise ratio for each of the six sentences was made to establish a set of expected results. In a differential quantizer, the SNR may be computed by [6]

$$\mathrm{SNR} = \frac{\sigma_x^2}{\sigma_e^2} = \frac{\sigma_x^2}{\sigma_d^2} \cdot \frac{\sigma_d^2}{\sigma_e^2} = G_p \cdot \mathrm{SNR}_Q \tag{36}$$

where G_p is the gain due to differential coding. SNR_Q is just the SNR of the quantizer. For a first order predictor as used in the simulations, the SNR gain, G_p can be approximated by

$$G_p = \frac{1}{1 - \alpha_1^2} = 3.84 \tag{37}$$

for $\alpha^1 = 0.86$. Expressed in decibels, $G_p = 5.84$. Thus we can expect almost a 6 dB increase over the PCM coder SNR. To determine values for SNR_Q, equation (32) was used with the standard deviation values inserted from Table 12. Table 13 was constructed from these expressions as an estimate of ADPCM coder performance with a uniform quantizer. Similar estimations of Laplacian and gamma quantizer results were not developed. The variation of estimated results

$$\Delta = SNR_{max} - SNR_{min} = 0.65 \text{ dB}$$

follows from the similarity of the error file's variances. Ideally, for a positive gain, G_p, due to the differential prediction, we would expect $\sigma_d^2 < \sigma_x^2$. Comparing the estimated variance in Tables 2 and 12 shows that σ_d^2 for SE2 is actually greater than σ_x^2 of S2. Thus, we see that the choice of predictor coefficient α_1 was not acceptable for all six sentences.

In the comparison of ADPCM coder simulation results, only the SNR from ADPCOD and the NIT from OPT1 were used. Also, the coded output speech file was used in the listening tests.

Appendix Tables A16 and A17 list the SNR results for each of the 240 coded speech files. Tables A18 and A19 present the MSE from equation (17) of the quantizer from PCM coding of the error files. The MSE data is presented only to provide documentation of the reduction of quantizer mean squared error with each additional quantization level.

Table 13. Estimated ADPCM Speech Coder Results Using Uniform Quantization

File Name	Number of Quantization Levels 4	8	16	32	64
S1	4.20	10.20	16.20	22.20	28.20
S2	3.56	9.56	15.56	21.56	27.56
S3	4.21	10.21	16.21	22.21	28.21
S4	3.76	9.76	15.76	21.76	27.76
S5	3.75	9.75	15.75	21.75	27.75
S6	3.61	9.61	15.61	21.61	27.61

Figure 27 is a graph of the maximum and minimum SNR_F at each number of output levels for uniform and speech-histogram (optimum) quantized speech. Both the curves on the plot are relatively smooth with almost constant slope. The fact that the uniform curves are smooth can be attributed to the change of speech file zero amplitude samples to non-zero samples in the error file due to the adaptive differential nature of the error file. A slight decrease in slope can be seen in both the optimum quantizer curves which, as in the PCM simulations, can be attributed to errors in computation of the near-zero decision and reconstruction levels. Table 14 presents a comparison of the uniform, Laplace and gamma quantized results with the optimum results. As in Table 10, entries represent difference in decibels between the comparable coder SNR_F results. For example, the -0.10 given for a 3-level Laplacian coder of S2 indicates the Laplacian quantizer gave a 0.10 dB greater SNR than the optimum 3-level quantizer designed for and used on the same sentence. On the average, the optimum ADPCM coder gives 1.5 dB greater SNR improvement over uniform ADPCM coders than the optimum PCM coders give over uniform PCM coders. From the table we can see that the Laplace, gamma and optimum quantizers approach each other in performance as the number of quantization levels increase beyond 32. This trend was also evident in the PCM coder results. Results from the Laplacian quantizer indicate that optimum quantizer improvements over Laplacian quantizer performance are generally in the less than one dB range, with some sentences coded better by Laplacian quantizers than by optimum quantizers. On an average, the optimum quantizer gives superior results, but only 0.35 to 1.1 dB better than the fixed quantizers

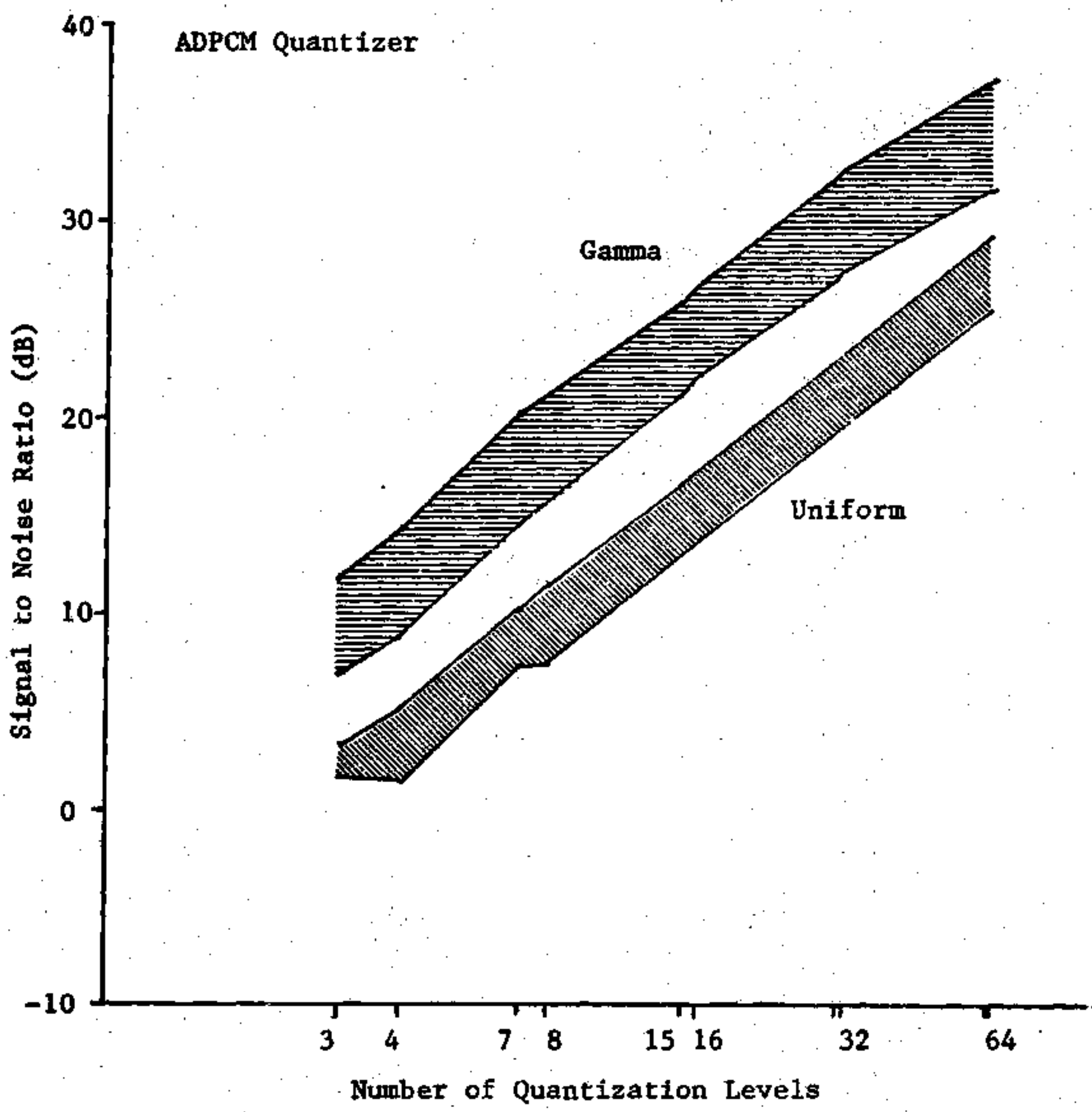


Figure 27. kange of Coder SNR for ADPCM Coded Speech Files S1 - S6

Table 14. Uniform, Laplacian and Gamma ADPCM Coder SNR Comparison

Quantizer Type	NLOUT	S1	S2	S3	S4	S5	S6	Ave.
Uniform	3	8.83	5.28	7.66	8.42	6.46	7.75	7.40
	4	9.14	7.55	8.32	9.23	7.89	8.11	8.37
	7	9.64	7.32	9.50	10.04	8.74	8.86	9.02
	8	9.62	8.13	9.55	9.92	8.80	8.77	9.13
	15	9.35	8.07	8.90	9.34	8.25	8.89	8.80
	16	9.04	8.32	9.28	9.49	8.56	8.84	8.92
	31	8.91	7.94	9.15	9.21	8.35	8.37	8.66
	32	8.94	7.91	9.18	9.16	8.18	8.43	8.63
	63	8.03	6.08	8.50	7.67	5.81	7.00	7.18
	64	8.01	5.83	8.44	7.40	6.49	6.99	7.19
AVE(3→32)		9.18	7.57	8.94	9.35	8.15	8.50	8.62
AVE(3→64)		8.95	7.24	8.85	8.99	7.75	8.20	8.33
Laplace	3	-0.10	0.11	0.11	-0.05	0.57	0.38	0.17
	4	-0.55	-0.51	-0.84	-0.75	-0.18	-0.65	-0.58
	7	0.89	-0.34	0.55	1.03	0.06	0.38	0.43
	8	0.97	-0.53	0.67	1.07	0.10	0.11	0.40
	15	1.08	0.09	0.69	0.59	-0.06	0.73	0.52
	16	0.89	0.09	1.09	0.84	0.38	0.58	0.65
	31	0.89	0.00	1.15	0.87	0.17	0.42	0.58
	32	0.85	0.11	1.07	0.83	0.10	0.57	0.59
	63	-0.05	-1.70	0.40	-0.61	-2.12	-0.83	-0.82
	64	0.04	-1.81	0.32	-1.00	-1.35	-0.96	-0.79
AVE(3→32)		0.62	-0.12	0.56	0.55	0.14	0.32	0.32
AVE(3→64)		0.49	-0.45	0.52	0.28	-0.23	0.07	0.12
GAMMA	3	0.05	-0.79	-0.53	-0.53	-1.00	-0.35	-0.53
	4	1.05	-1.08	0.15	0.79	-0.32	-0.20	0.07
	7	2.42	0.28	2.45	2.57	1.04	1.06	1.64
	8	2.40	0.35	2.40	2.70	1.36	1.21	1.74
	15	2.23	0.75	1.66	2.01	1.13	1.43	1.54
	16	2.13	1.09	2.24	2.46	1.49	1.69	1.85
	31	2.06	0.64	2.10	2.02	1.26	1.05	1.52
	32	2.06	0.77	2.29	2.04	0.99	1.15	1.55
	63	0.87	-1.26	1.48	0.27	-1.43	-0.22	-0.05
	64	0.87	-1.43	1.54	0.25	-0.63	-0.24	0.06
AVE(3→32)		1.80	0.25	1.60	1.76	0.74	0.88	1.17
AVE(3→64)		1.61	-0.07	1.58	1.46	0.39	0.66	0.94

considered here. For an ADPCM coder with a larger number of predictor coefficients, the error file distribution will approach gaussian, hence one would expect gaussian quantization to give good results. This test was not performed. It is important to note that the Laplacian and gamma quantizers were adapted to a particular sentence by use of error file variance as a histogram parameter, thus the analytical histogram results seen here will be better than one would get if the same Laplace or gamma quantizer were used for all six sentences. The estimated uniform quantizer results of Table 15 were found to be, on the average, 0.3 dB less than the actual simulation SNR results, thus, for a uniform quantizer, the ADPCM coder performed as expected. The results from sentence S2 were not as different from the other ADPCM results as was seen in a comparison of PCM coder results.

Table 15 gives a list of number of algorithm iterations for uniform, Laplace, gamma and optimum quantizers of 2 to 6 bits. The entries in this table are very similar to the entries in Table 11, supporting the assertion made in Chapter IV that NIT is not very dependent upon histogram shape or variance. The NIT results in Table 15 support the NIT estimates given in the Convergence Test section of Chapter IV.

Listening Tests and Results

A set of listening tests was performed on the coder output speech to determine whether minimization of the quantizer mean squared error (thus maximizing the output signal to noise ratio) results in audible improvements. All 240 PCM coder output files and all 240 ADPCM coder

Table 15. Number of Iterations to Optimum ADPCM Quantizer

Histogram Type		Number of Iterations 4	8	16	32	64
Uniform	MAX	10	31	90	226	564
	MIN	10	31	90	226	564
	AVE	10	31	90	226	564
Laplacian	MAX	23	77	245	763	1000
	MIN	23	76	240	740	1000
	AVE	23	76	242	752	1000
Gamma	MAX	24	79	257	822	1000
	MIN	23	78	249	752	1000
	AVE	23	78	253	794	1000
Optimum	MAX	49	172	271	453	1000
	MIN	26	50	120	324	625
	AVE	37	86	166	415	894

output files were evaluated by a single listener to provide the subjective results of these tests.

Two classes of tests were conducted. The first test consisted of comparing the uniform, Laplacian, gamma and optimally quantized output of each number of quantization levels for each of the six sentences. Performance of the coder was ranked in descending order for each group of four quantizers. Two sets of results were obtained from this class of test. The first set of results came from evaluation of the PCM coder output speech. The second set, from the ADPCM coder output. A second class of tests considered only the ADPCM coder output. A single sentence was chosen from the six and all reasonable combinations of uniform and optimally quantized speech were compared.

A symbology is developed to aid in the presentation of the test results. Each of the four types of quantizers used in a speech coder will be referred to by the first letter of the quantizer name. Thus, the output speech file from a coder employing a gamma quantizer will be called the gamma or G file. The other references are U, L and O for uniform, Laplacian and optimum quantizers. A number from the set of possible quantizer output levels will be used as a suffix to the quantizer type letter to describe the number of levels in a particular quantizer. Finally, the input speech file name; S1, S2,..., etc. used as a prefix to the quantizer letter will describe the sentence from which an output file was derived. As an example, S3L16 refers to the output file from a coder employing a 16-level Laplacian quantizer operating upon input speech file S3. Coder type, ADPCM or PCM, will be understood in a given application.

The first class of tests consisted of comparisons of 60 groups of four files each. As a result of six A-B comparisons of the four files, they were ranked in order of decreasing distortion. Each pair of files were repeated four times for evaluation. As an example, files S3U15, S3L15, S3G15 and S3O15 were evaluated for the least distorted of each of the six pairs;

S3U15 versus S3L15

S3U15 versus S3G15

S3U15 versus S3O15

S3L15 versus S3G15

S3L15 versus S3O15

S3G15 versus S3O15

For each pair, ranking and comments were recorded. Similar comparisons were performed for each of the 10 number of levels sets, and for each of the six sentences. Tables 16 and 17 present the results of these tests. Within each column on the tables, there are ten sets of two rows. The top row of each set represents the ranking (least distorted = 1) based upon listening test results. The second row of each set represents the ranking based upon SNR calculations.

Several general comments can be made from the results of the PCM coder listening tests. Generally, coders with 2^B-1 quantization levels have a much lower noise floor than coders with 2^B quantization levels. However, the quantizer with more levels produces less distorted speech due to a greater amount of information in the output file. Quantization of three or four levels is severely distorted and therefore not of interest. Coders with 7 to 16 levels of quantization generally perform

Table 16. Performance of PCM Coder for Six Sentences

Number Of Levels	S1 1 2 3 4	S2 1 2 3 4	S3 1 2 3 4	S4 1 2 3 4	S5 1 2 3 4	S6 1 2 3 4
(SUB)3	L G O U	L G O U	L O G U	L O G U	L G O U	L G O U
(OBJ)	O G L U	O G L U	O G L U	O G L U	O G L U	O G L U
4	L G O U	G L O U	L G O U	O L G U	G L O U	L G O U
	O G L U	O G L U	O G L U	O G L U	O G L U	O G L U
7	O L G U	L G O U	O G L U	O G L U	G L O U	L G O U
	O L G U	O G L U	O G L U	O G L U	O G L U	O G L U
8	L G O U	L G O U	G L O U	O G L U	O L G U	G L O U
	O G L U	O G L U	O G L U	O G L U	O G L U	O G L U
15	O L G U	O L G U	O L G U	O G L U	O G L U	O G L U
	O L G U	O G L U	O L G U	O G L U	O G L U	O G L U
16	O L G U	O L G U	O G L U	O L G U	O G L U	O G L U
	O G L U	O G L U	O G L U	O G L U	O G L U	O G L U
31	O G L U	O L G U	O G L U	O G L U	L O G U	L O G U
	O L G U	O G U L	O G L U	O G L U	G O L U	O G L U
32	O G L U	O L G U	O G L U	O G L U	O G L U	O G L U
	O G L U	O G L U	O G L U	O G L U	O G L U	O G L U
63	G L U O	G L O U	G L O U	O G L U	G O L U	G L O U
	G L O U	O G U L	G L O U	G L O U	G L O U	G O L U
64	O L G U	O G L U	L O G U	O G L U	G O L U	O G L U
	G L O U	O G U L	G L O U	G L O U	G L O U	G O L U

O = Optimum Quantizer
L = Laplacian Quantizer
G = Gamma Quantizer
U = Uniform Quantizer
OBJ = Objective Results
SUB = Subjective Results

Table 17. Performance of ADPCM Coder for Six Sentences

Number Of Levels	S1	S2	S3	S4	S5	S6
	1 2 3 4	1 2 3 4	1 2 3 4	1 2 3 4	1 2 3 4	1 2 3 4
(SUB)3	O L G U	O L G U	O L G U	O L G U	L O G U	O L G U
(OBJ)	L O G U	G O L U	G O L U	G L O U	G O L U	G O L U
4	O L G U	L O G U	O L G U	O L G U	O L G U	O L G U
	L O G U	G L O U	L O G U	L O G U	G L O U	L G O U
7	O L G U	O G L U	O L G U	O L G U	L O G U	O L G U
	O L G U	L O G U	O L G U	O L G U	O L G U	O L G U
8	O L G U	O L G U	O L G U	O L G U	O L G U	O L G U
	O L G U	L O G U	O L G U	O L G U	O L G U	O L G U
15	O L G U	O L G U	O L G U	O L G U	O L G U	O L G U
	O L G U	O L G U	O L G U	O L G U	L O G U	O L G U
16	O L G U	O L G U	O L G U	O G L U	O L G U	O L G U
	O L G U	O L G U	O L G U	O L G U	O L G U	O L G U
31	O L G U	O L G U	O L G U	O G L U	O G L U	O L G U
	O L G U	O L G U	O L G U	O L G U	O L G U	O L G U
32	O L G U	O L G U	O L G U	G O L U	O L G U	O L G U
	O L G U	O L G U	O L G U	O L G U	O L G U	O L G U
63	O L G U	O G L U	L O G U	L O G U	L O G U	O L G U
	L O G U	L G O U	O L G U	L O G U	L G O U	L G O U
64	O L G U	O L G U	O L G U	O L G U	L O G U	O L G U
	O L G U	L G O U	O L G U	L O G U	L G O U	L G O U

O = Optimum Quantizer
L = Laplacian Quantizer
G = Gamma Quantizer
U = Uniform Quantizer
(OBJ) = Objective Results
(SUB) = Subjective Results

better with optimum quantization. Coders with greater than 31 quantization levels perform equally as well with Laplace, gamma or optimum quantization. The optimum quantizer generally has the lowest noise, but has another distortion related to its inability to accurately code phonetic stops. The subjective results of Table 17 show that optimum quantization was not as acceptable as the SNR calculations indicate.

The results from ADPCM listening tests suggest that optimum quantization performs better on the error files than it does on the speech files. Table 17 indicates that optimum quantization generally gives the least distorted output of the quantizers tested. The optimum quantizer in an ADPCM coder does not exhibit the same inability to code stops as does the optimum PCM coder. Optimum, gamma and Laplacian quantizers of 63 and 64 levels were almost indistinguishable from their coded output files. As with the PCM coder, the uniformly quantized coder performed as well as other coders with one fewer bit of quantization.

In the second class of tests, we chose to study sentence S4. A-B comparisons of uniform and optimum quantizers within an ADPCM coder were made for all interesting number of levels combinations. Each pair was repeated four times for evaluation. A total of 45 pairs were considered. Table 18 lists the tests that were performed and the results of the comparisons. An O on the table indicates the optimum quantizer performed better, while a U indicates the uniform quantizer was superior. It can be concluded that always, the optimum quantizer of 2^B levels performed better than a uniform quantizer of 2^{B+1} levels.

Table 18. Comparison of Uniform and Optimum ADPCM Coders

Type		Optimum									
	NLOUT	3	4	7	8	15	16	31	32	63	64
	3	O									
	4	O									
	7	O	O								
	8	O	O	O							
Uniform	15	U	U	O	O						
	16	U	U	O	O	O					
	31	U	U	U	U	O	O				
	32	U	U	U	U	O	O	O			
	63	U	U	U	U	U	O	O	O		
	64	U	U	U	U	U	O	O	O	O	

This test supports the SNR data from the ADPCM coder simulations in showing that optimum quantization gives results at least one bit better than a uniform quantizer applied to the same signal.

Discussion of Simulations Results

From the combined objective and listening test results of the PCM coder simulations, some interesting conclusions can be drawn. Based strictly upon signal to noise ratio measurements, the uniform quantizer averaged 8.9 dB less SNR than the Laplacian, gamma or optimum quantizers of similar number of levels. The listening test supports this average by the indication that uniform quantization performs approximately as well as other quantizers of one less bit. Coders with $2^B - 1$ quantization levels generally had greater audible and computed signal to noise ratios than quantizers of 2^B levels. The 2^B level quantizers were superior in audible performance due to less distortion of the speech. Objective measures indicate optimum quantization was superior in most of the coders tested. The listening tests, however indicate that gamma quantization was superior in several instances due to a greater amount of perceived distortion in the optimally quantized speech. Based upon the optimum quantized coder output and the time required to compute a quantizer characteristic, we will limit consideration of PCM coders to those employing 8, 16 and 32 level quantizers. With this constraint, average improvements in measured signal to noise ratio are given as

Optimum 9.6 dB improvement over uniform

Optimum 2.7 dB improvement over Laplacian

Optimum 1.2 dB improvement over gamma.

It was found that the input speech files; S1, S2,..., etc. Were indistinguishable from the 64-level Laplacian, gamma or optimally quantized coder outputs. We saw in Chapter IV that the location of reconstruction and decision levels in Laplace and gamma quantizers become very similar for quantizers of a large number of levels. This similarity in quantization level location causes a similarity in performance that makes the output speech files indistinguishable from one another.

Combined objective and listening test results from the ADPCM coder simulations provide more insight into the use of an optimum quantizer. As for the PCM coder, the uniform quantizers of 2^B levels performed as well as Laplacian, gamma or optimum quantizers of 2^{B-1} levels in subjective and objective tests. Laplace, gamma and optimum quantizers averaged 8.1 dB SNR improvement over a uniform quantizer of the same number of levels. In general, ADPCM coders of 2^B levels performed as well as PCM coders of 2^{B+1} levels for all quantizer types. Little audible difference between quantizers of 2^B levels and 2^B-1 levels was detected. This is quite different from the PCM coder results. The optimum quantizers showed only a marginal improvement over Laplace and gamma quantizers when comparing SNR improvements. The listening tests show that optimum quantization is clearly superior to Laplace or gamma quantization for most of the coders tested. For the same reasons as discussed in the previous paragraph, we will limit consideration of ADPCM speech coders to those employing 8, 16 and 32 levels of quantization. With this constraint, the average improvements based upon measured SNR are given as

Optimum 8.9 dB improvement over uniform

Optimum 0.5 dB improvement over Laplacian

Optimum 1.7 dB improvement over gamma.

These average improvement numbers indicate that Laplace and optimum quantizers in ADPCM coders are very similar. The listening tests support this similarity, but also indicate that optimum is generally better than the 0.5 dB figure indicates. Little audible difference was detected between Laplace, gamma and optimum quantizers of 63 or 64 levels. At a large number of quantization levels (NLOUT > 32), it was shown in Chapter IV that differences in quantization level locations become small, contributing to the similarity in coder performance.

CHAPTER VI

CONCLUSIONS

As in many engineering problems, an unconstrained solution is not possible. This study shows that under certain conditions, optimum quantization is worth consideration.

In all of the simulations we considered, OPT1 showed no divergence tendencies in obtaining the minimum MSE quantizer characteristic. This represents a substantial improvement over operation of the Max algorithm.

Based upon the time required to compute an optimum quantizer from a histogram of the input signal by OPT1, only quantizers of 2, 4, 8, 16 and 32 levels can reasonably be considered. From the PCM and ADPCM coder listening test results, it was shown that two and four level optimum quantization is useless due to the low ensuing signal to noise ratio.

Optimum quantization applied to a PCM speech coder may be of only marginal use when performance is compared with Laplace or gamma quantization. It should be noted, however, that the Laplace and gamma quantizers used in this study were computed for a specific sentence, and not a general quantizer characteristic. Also, in this study we considered only a single block length. It is possible that when optimum quantization is applied to blocks of length less than two seconds, a greater improvement over fixed quantizers can be achieved. When the optimum quantizer performance is compared with general Laplace or gamma quantizer performance, one may see a greater improvement than these simulations have shown. With respect to signal to noise ratio, use of the optimum quantizer should result in 1.2 dB to 2.7 dB improvement over other non-uniform quantization techniques.

Use of an optimum quantizer in ADPCM speech coders for quantizers of 4, 8, 16 and 32 levels will result in an audible performance improvement over use of Laplacian or gamma quantizers. In the ADPCM coder, optimum quantization is only marginally superior with respect to signal to noise ratio measurements, but subjectively there is a noticeable improvement. As in the PCM coder, comparisons of optimum quantization with general Laplace or gamma distributed quantizers should show optimum quantizer performance better than this study indicates.

From the Convergence test simulations it was found that the maximum entropy start sequence, which is relatively simple to compute, is a fair approximation to the minimum mean square error quantizer characteristic for large (≥ 16) number of output levels.

In the Parameter Study section it was shown that a constraint is placed upon the number of quantization levels for which an optimum quantizer may be computed by the number of bins in the histogram. In general, the histogram must have at least 32 times as many bins than there are levels in the quantizer for the greatest amount of MSE minimization to be achieved.

The speech histograms used in this study were computed from large enough samples of speech that there were few bins with zero counts in them. As the length of the block of data to be quantized decreases, the probability for holes in the histogram will increase. It is unknown at this point how well OPT1 will perform on histograms with large holes in them. This question should be investigated to determine if use of an optimum quantizer on shorter blocks is possible.

Extensive subjective analysis of the speech coder output files should be conducted to provide results that are not biased by one listener's preferences. Comparisons with coders employing general purpose Laplacian and gamma quantization should also be included. It was seen that low quality of the input speech files may have contributed to the convergence of results for quantizers of a large number of levels. Before extensive subjective analysis is performed, high quality input speech should be coded to provide the coder output files.

The major emphasis was put on comparing optimum quantization with quantizers designed for speech. This implies that the speech has been characterized by some analytical amplitude probability distribution such as Laplacian or gamma. An interesting extension of this study would be to apply optimum quantization to coders operating upon signals that have not been characterized by some analytical distribution. In that application, the use of optimum quantization should prove superior to uniform quantization.

APPENDIX

APPENDIX A

MNEMONICS AND SYMBOLS

Symbols Used in Thesis

A	Area of histogram region defined by two adjacent decision levels
a(n)	Windowed energy measure of ADPCM difference signal
a_n	Arbitrary histogram abscissa distance
b	Algorithm iteration counter
C	Convergence limit
c(n)	ADPCM coder difference signal
D	Quantizer induced distortion
d(n)	Gain-controlled ADPCM coder difference signal
$\hat{d}(n)$	ADPCM coder quantizer output
e(n)	Quantizer error sequence defined by (1)
e_s	Average percent difference in quantization levels, a symmetry measure
f	Number of samples per energy frame
G_p	ADPCM coder gain due to differential coding
i	Index
j	Index
K	Scaling constant
k	Index
L	Number of samples in x(n) input file

M	Number of bins in histogram
N	Number of quantizer reconstruction or quantization levels
$p(x)$	Probability density function
p_j	Number of counts in the j^{th} bin of a histogram
r	Number of predictor coefficients
T	Sample period
$x(n)$	Sequence of numbers representing a sampled signal, input file
$\tilde{x}(n)$	Predictor output signal of ADPCM coder
$\hat{x}(n)$	Predictor input signal to ADPCM coder
x_j	Integer histogram abscissa position value
x_{max}	Highest amplitude sample, ≤ 32767
x_{min}	Lowest amplitude sample, ≥ -32768
x_N	Same as x_{max}
x_0	Same as x_{min}
$y(n)$	Quantizer output sequence
y_j	The j^{th} (of N) output reconstruction level
α_k	The k^{th} predictor coefficient value
Δ	The distance between a_n and a_{n-1}
η	Statistical mean of a speech file
σ_d^2	ADPCM coder difference signal variance
σ_e^2	Statistical variance of quantization error file
σ_x	Standard deviation of input speech file
σ_x^2	Statistical variance of input speech file

Mnemonics Used in Thesis

ADPCM	Adaptive differential pulse code modulation
ADPCOD	ADPCM coder simulation program
CTST	Convergence test limit
DMIN	Maximum reconstruction level difference computed at each iteration
KBPS	Kilo-bits per second, an information transfer rate
MSE	Mean squared error
MSE	MSE computed from output file, related to SNR
MSE	MSE computed from histogram, equation (14)
NBIN	Number of bins in histogram
NIT	Number of optimum quantizer algorithm iterations
NLOUT	Number of quantization levels
NVAR	Number of standard deviations to full range of histogram abscissa
OPT1	Optimum quantizer calculation and PCM coder main program
PCM	Pulse code modulation
SNR	Signal to noise ratio
SNR	SNR computed from output file, equation (28)
SNR	Quantizer SNR computed from equation (29)
SPCHSTAT	Program to estimate statistics of an integer file
THTLB	Subroutine of OPT1 that creates analytical histograms
TIM	Estimated time required to perform one iteration of optimum quantizer algorithm
TIME	Time required for NIT iterations of the algorithm
VAR	Variance of the input speech or error file, to OPT1

APPENDIX B

UNIFORM QUANTIZER MEAN SQUARED ERROR CALCULATION

We wish to derive a relationship for computing the MSE of a uniform quantizer. For probability density function, $p(x) = 1$, for all x such that $x_o \leq x \leq x_N$, we solve for MSE by

$$MSE = \frac{\sum_{k=1}^{N} \int_{x_{k-1}}^{x_k} (y_k - x)^2 p(x)\,dx}{\int_{x_o}^{x_N} p(x)\,dx} .$$

Assuming a symmetric distribution such that $x_o = -x_N$, we have

$$MSE = \frac{1}{2x_N} \sum_{k=1}^{N} \int_{x_{k-1}}^{x_k} (y_k - x)^2 p(x)\,dx .$$

The value of the integral is the same for each value of k (this is true only in the uniform distribution) hence,

$$MSE = \frac{N}{2x_N} \int_{x_o}^{x_1} (y_1 - x)^2 dx$$

$$= \frac{N}{2x_N} \left[y_1^2(x_1 - x_o) - y_1(x_1^2 - x_o^2) + \tfrac{1}{3}(x_1^3 - x_o^3) \right] .$$

It is easily seen that

$$y_1 = \frac{x_N}{N}(1-N) \;, \quad y_k = \frac{x_N}{N}(2k-N-1)$$

$$x_1 = \frac{x_N}{N}(2-N) \;, \quad x_k = \frac{x_N}{N}(2k-N)$$

and

$$x_o = -x_N \;.$$

Substituting into the equation for MSE, after some manipulation, we see

$$\mathrm{MSE} = \frac{{x_N}^2}{3N^2} \quad \text{for } N = 1,\ 2,\ 3,\ \ldots$$

$$= \text{number of quantization levels} \;.$$

APPENDIX C

LAPLACIAN QUANTIZER COMPUTATIONS

We wish to solve the optimum quantizer expressions for the reconstruction and decision levels of a Laplacian quantizer. Only a 2 and a 4-level quantizer will be considered since the computation becomes quite tedious for quantizers of a greater number of levels. Also the mean squared error of the quantizer will be computed. As a result of these calculations two things will be noticed. First, the theoretical results derived here are quite different from the results of Paez and Glisson. Second, for a quantizer that has a nonuniform transfer characteristic, the contribution to the total mean squared error is not equal for each pair of decision levels.

The Laplacian function is given as

$$p(x) = \frac{1}{\sqrt{2}} \; e^{-\sqrt{2}|x|} \tag{1}$$

The quantizer mean squared error is found by

$$\mathrm{MSE} = \frac{\displaystyle\sum_{k=1}^{N} \int_{x_{k-1}}^{x_k} (x - y_k)\; p(x)dx}{\displaystyle\int_{x_0}^{x_N} p(x)dx} \tag{2}$$

And the decision and reconstruction levels for an optimum quantizer are computed by

$$x_k = \frac{1}{2}(y_k + y_{k+1}) \tag{3}$$

$$y_k = \frac{\displaystyle\int_{x_{k-1}}^{x_k} xp(x)dx}{\displaystyle\int_{x_{k-1}}^{x_k} p(x)dx} \tag{4}$$

2-Level Quantizer

For a 2-level Laplacian quantizer, we can assign the decision levels and then solve for the reconstruction levels. Due to the symmetry of the Laplacian function, only one reconstruction level must be computed, thus we begin with

$$x_0 = -\infty$$

$$x_1 = 0$$

$$x_2 = \infty$$

Solving first the denominator of (4), we have

$$\int_{-\infty}^{0} \frac{1}{\sqrt{2}} e^{-\sqrt{2}|x|} dx = \frac{1}{\sqrt{2}} \left[\frac{1}{\sqrt{2}} e^{+\sqrt{2}x} \Big|_{-\infty}^{0} \right] = \frac{1}{2}$$

Now, solving (4) for y_1,

$$y_1 = 2 \int_{-\infty}^{0} x \frac{1}{\sqrt{2}} e^{-\sqrt{2}|x|} dx = \sqrt{2} \int_{-\infty}^{0} x\, e^{\sqrt{2}x} dx$$

$$= \sqrt{2}\left[\left(\frac{x}{\sqrt{2}} - \frac{1}{2}\right) e^{\sqrt{2}x}\Big|_{-\infty}^{0}\right] = -\frac{1}{\sqrt{2}}$$

then

$$y_1 = -\frac{1}{\sqrt{2}}$$

$$y_2 = +\frac{1}{\sqrt{2}}$$

Now, to compute the MSE, we solve the denominator term of (2)

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2}} e^{-\sqrt{2}|x|} dx = 1$$

Due to symmetry of the Laplacian function, contribution to the MSE from the region $x_0 \leq x \leq x_1$ is equal to the contribution from the region $x_1 \leq x \leq x_2$, thus, we solve for only one region and double the result.

$$\text{MSE} = 2 \int_{-\infty}^{0} (x + \frac{1}{\sqrt{2}})^2 \frac{1}{\sqrt{2}} e^{\sqrt{2}x} dx$$

$$= \sqrt{2}\left[\left(\frac{x^2}{\sqrt{2}} + \frac{1}{2\sqrt{2}}\right) e^{\sqrt{2}x}\Big|_{-\infty}^{0}\right] = \frac{1}{2}$$

<u>4-Level Quantizer</u>

For a 4-level Laplacian quantizer, we begin with three decision levels,

$$x_0 = -\infty$$

$$x_2 = 0$$

$$x_4 = \infty$$

From symmetry of the distribution, we know the remaining decision and reconstruction levels have the following relationships

$$x_1 = -x_3$$

$$y_1 = -y_4$$

$$y_2 = -y_3$$

To compute the quantizer decision levels, we must solve equations (3) and (4) for x_3, y_3 and y_4.

We first solve (4) for y_4,

$$y_4 = \frac{\int_{x_3}^{x_4} x \frac{1}{\sqrt{2}} e^{-\sqrt{2}x} dx}{\int_{x_3}^{x_4} \frac{1}{\sqrt{2}} e^{-\sqrt{2}x} dx}$$

$$= \frac{\left(\frac{x}{\sqrt{2}} + \frac{1}{2}\right) e^{-\sqrt{2}x}\Big|_{x_3}^{\infty}}{\frac{1}{\sqrt{2}} e^{-\sqrt{2}x}\Big|_{x_3}^{\infty}} = \frac{\left(\frac{x_3}{\sqrt{2}} + \frac{1}{2}\right)}{\frac{1}{\sqrt{2}}}$$

$$y_4 = x_3 + \frac{1}{\sqrt{2}} \tag{5}$$

Now, solve (3) for y_3 using the y_4 computed in (5).

$$x_3 = \frac{1}{2}(y_3 + y_4)$$

$$= \frac{1}{2}\left(y_3 + x_3 + \frac{1}{\sqrt{2}}\right)$$

$$y_3 = x_3 - \frac{1}{\sqrt{2}} \qquad (6)$$

solving (4) for y_3,

$$y_3 = \frac{\int_{x_2}^{x_3} x \frac{1}{\sqrt{2}} e^{-\sqrt{2}x} dx}{\int_{x_2}^{x_3} \frac{1}{\sqrt{2}} e^{-\sqrt{2}x} dx}$$

$$= \frac{\left(\frac{x}{\sqrt{2}} + \frac{1}{2}\right) e^{-\sqrt{2}} \Big|_0^{x_2}}{\frac{1}{\sqrt{2}} e^{-\sqrt{2}x} \Big|_0^{x_3}} = \frac{\frac{1}{\sqrt{2}} - \left(x_3 + \frac{1}{2\sqrt{2}}\right) e^{-\sqrt{2}x_3}}{1 - e^{-\sqrt{2}x_3}} \qquad (7)$$

Now solve (6) and (7) for x_3,

$$x_3 - \frac{1}{\sqrt{2}} = \frac{\frac{1}{\sqrt{2}} - \left(x_3 + \frac{1}{2\sqrt{2}}\right) e^{-\sqrt{2}x_3}}{1 - e^{-\sqrt{2}x_3}}$$

$$x_3 - \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} e^{-\sqrt{2}x_3} = \frac{1}{\sqrt{2}} - \frac{1}{2\sqrt{2}} e^{-\sqrt{2}x_3}$$

$$x_3 + \sqrt{2}\, e^{-\sqrt{2}x_3} - \sqrt{2} = 0 \tag{8}$$

Equation (8) is solved iteratively for the x_3 that satisfies the equality. It was found that

$$x_3 = 1.12686252$$

Now, substitute x_3 into (5) for y_4, and x_3 into (6) for y_3,

$$y_4 = 1.12686 + \frac{1}{\sqrt{2}} = 1.8339693$$

$$y_3 = 1.12686 - \frac{1}{\sqrt{2}} = 0.41975574$$

Now we shall compute the mean squared quantizer error. Due to symmetry of the Laplacian function, the contribution to the MSE from the region $x_0 \leq x \leq x_1$ is equal to the contribution from the region defined by $x_3 \leq x \leq x_4$. Also, the contribution to the MSE from the region $x_1 \leq x \leq x_2$ is equal to the contribution from the region defined by $x_2 \leq x \leq x_3$. With this simplification the mean squared error can be computed by

$$\text{MSE} = \frac{2\int_{x_2}^{x_3} (y_3 - x)^2 p(x)\,dx + 2\int_{x_3}^{x_4} (y_4 - x)^2 p(x)\,dx}{\int_{x_0}^{x_4} p(x)\,dx} \tag{9}$$

we have shown the denominator term is unity, then solving the first integral of (9)

$$2\int_{x_2}^{x_3}(y_3 - x)^2 p(x)dx = \sqrt{2}\int_{0}^{x_3}(y_3 \quad - 2y_3x + x^2)e^{-\sqrt{2}x}dx$$

$$= e^{-\sqrt{2}x}\left[x^2 + (\sqrt{2} - 2y_3)x + (y_3^{\,2} - \sqrt{2}y_3 + 1)\right]\Bigg|_0^{x_3}$$

$$= (1 - \sqrt{2}y_3 + y_3^{\,2}) - (x_3^{\,2} + x_3(1 - y_3\sqrt{2})\sqrt{2} + 1 - y_3\sqrt{2} + y_3^{\,2})e^{-\sqrt{2}x_3}$$

Substitute in values for y_3 and x_3,

$$2\int_{x_2}^{x_3}(y_3 - x)^2 p(x)dx = 0.074600946$$

Solving the second integral of (9)

$$2\int_{x_3}^{x_4}(y_4 - x)^2 p(x)dx = \sqrt{2}\int_{x_3}^{\infty}(y_4^{\,2} - 2y_4x + x^2)e^{-\sqrt{2}x}dx$$

$$= e^{-\sqrt{2}x}\left[x^2 + (\sqrt{2} - 2y_4)x + (y_4^{\,2} - \sqrt{2}y_4 + 1)\right]\Bigg|_{x_3}^{\infty}$$

$$= \left[x_3^{\,2} + \sqrt{2}x_3(1 - y_4\sqrt{2}) + 1 - \sqrt{2}y_4 + y_4^{\,2}\right]e^{-\sqrt{2}x_3}$$

Substitute in values for x_3 and y_4,

$$2\int_{x_3}^{x_4} (y_4 - x)^2 p(x)\,dx = 0.101593936$$

Then the total MSE is the sum of the two parts, or

$$MSE = 0.074600946 + 0.101593936$$

$$MSE = 0.176194881$$

for a four-level quantizer.

APPENDIX D

ESTIMATION OF COMPUTATION TIME

To obtain an estimate of the time required to compute a minimum mean squared error quantizer characteristic, the FORTRAN programs called by OPT1 were analyzed for the number of specific kinds of operations. No real effort was made to relate a FORTRAN statement to actual assembly level instructions from which a more accurate estimate could have been obtained.

In the following analysis, we first total all instructions in OPT1 subroutines that are repeated with each algorithm iteration. Next, the instructions performed once per quantizer characteristic will be listed. Finally some simplifications based upon execution times for similar instructions will be given to obtain the final estimates as they appear in the text. Only the instructions required to compute the quantizer characteristic will be considered.

The following program mnemonics are used as variables in the equations. The value of these variables will be set by a specific choice of program input parameters.

1) NBIN = number of bins in histogram

2) NLOUT = number of output levels in quantizer

3) NSPL = number of samples in a speech file

Many of the operations listed here are self explanatory. Those that require some explanation are listed below.

1) ABS = absolute value of a number

2) AND = boolean AND function

3) FLOAT = change from integer to real number

4) IF = comparison of two things, used in loops and tests

5) IFIX = change from real to integer number

6) ISZ = increment and skip, used in DO loops and for jumps

7) RDBLK = read in 256 integer words from disk

8) WRBLK = write 256 integer words to disk

Operations for One Iteration

The following operations, listed by subroutine, are performed each time the algorithm performs steps IV, V and VI of Figure 7.

QUAN

+,-	21(NLOUT) + 4(NBIN) - 3
x,÷	11(NLOUT) + 2(NBIN) - 2
=	17(NLOUT) + 2(NBIN) + 2
AND	4(NLOUT) - 2
IF	6(NLOUT) - 3
IFIX	2(NLOUT)
ISZ	2(NLOUT) + NBIN - 1

QUANER

+,-	2(NLOUT) + 2
ABS	NLOUT + 1
=	NLOUT + 1
IF	NLOUT + 1

ISZ	NLOUT + 1

<u>OPT1</u>

IF	1

The total number of operations for one iteration are then given as

+,-	23(NLOUT) + 4(NBIN) - 1
x,÷	11(NLOUT) + 2(NBIN) - 2
=	18(NLOUT) + 2(NBIN) + 3
AND	4(NLOUT) - 2
IF	7(NLOUT) - 1
ABS	NLOUT + 1
IFIX	2(NLOUT)
ISZ	3(NLOUT) + NBIN

<u>Operations for Each Quantizer</u>

The following operations, listed by subroutine, are performed once for each execution of OPT1. Operations with in the iteration loop are not included.

<u>OPT1</u>

+,-	2(NLOUT) + 2
x,÷	NLOUT + 1
=	2(NLOUT) + 5
FLOAT	NLOUT + 1

QNTIZESB

+,-	NLOUT + NSPL + 5
=	5(NLOUT)/2 + NSPL + 10
AND	(NLOUT)/2
IF	2(NLOUT)
ISZ	(NLOUT)/2 + NSPL
RDBLK	(NSPL)/256
WRBLK	(NSPL)/256

STATS

+,-	5(NSPL) + 3
x,÷	4(NSPL) + 1
=	3(NSPL) + 9
IF	4(NSPL)
ISZ	NSPL
RDBLK	(NSPL)/256

SRTSB

+,-	13(NBIN) + 1
x,÷	4(NBIN) + 3
=	7(NBIN) + 14
IF	3(NBIN)
ISZ	NBIN

The total number of operations for one run of OPT1 is given by

+,-	3(NLOUT) + 6(NSPL) + 13(NBIN) + 11
x,÷	NLOUT + 4(NSPL) + 4(NBIN) + 5
=	9(NLOUT)/2 + 4(NSPL) + 7(NBIN) + 38
AND	(NLOUT)/2
IF	2(NLOUT) + 4(NSPL) + 3(NBIN)
ISZ	(NLOUT)/2 + 2(NSPL) + NBIN
RDBLK	2(NSPL)/256
WRBLK	(NSPL)/256

<u>Execution Time Simplification</u>

From the composite lists of total number of operations given in the previous sections, an estimate of the computation time may be computed given values for NBIN, NLOUT, NSPL and NIT. To obtain a simpler relationship, we make some assumptions concerning the execution time of the listed instructions. These assumptions are;

+,-,x,÷,AND	= 10μ sec
=	= 4μ sec
ABS	= 10μ sec
IFIX	= 10μ sec
FLOAT	= 10μ sec
IF	= 10μ sec
ISZ	= 4μ sec

Thus, any instruction that requires access to one or more memory locations, an operation and return to memory location is assigned 10μ sec as an execution time. Any instruction that involves an increment or just a one way memory transfer is given 4μ sec as the execution time. With these assumptions, the relationships for execution times may be given as the product of the operation time and the number of operations. The resulting execution times are given in the following expressions.

<u>Time per Iteration (TIM)</u>

$$\text{TIM} = 564(\text{NLOUT}) + 72(\text{NBIN}) - 38 \qquad \mu \text{ sec}$$

<u>Time per Run (TIME)</u>

$$\text{TIME} = 85(\text{NLOUT}) + 164(\text{NSPL}) + 232(\text{NBIN}) + 312$$
$$+ \text{NIT}[564(\text{NLOUT}) + 72(\text{NBIN}) - 38] \qquad \mu \text{ sec}$$

APPENDIX E

SUPPLEMENTARY TABLES

The tables in this section contain much of the raw data resulting from the tests described in Chapter IV and the coder simulations described in Chapter V. Tables A, B and C contain quantizer decision and reconstruction level locations for Laplacian, Gamma and Gaussian quantizers. The numbers entered are based upon a maximum input signal amplitude range of -10.0 to +10.0. Tables A1 through A17 are refered to in the text. The data in these tables is used for support of some of the conclusions we have drawn.

Table A. Decision and Reconstruction Level Locations for 2, 4, 8, 16 and 32 Level Laplacian Quantizers

Level	OPTI	P & G	Esteban	Level	OPTI	P & G	Esteban
x_1	.7065	.707	.7085	y_1	0.0	0.0	0.0
x_1	1.8276	1.810	1.8349	y_1	1.1232	1.102	1.1281
x_2	.4188	.395	.4213				
x_1	3.0533	2.994	3.0774	y_1	2.3565	2.285	2.3752
x_2	1.6597	1.576	1.6732	y_2	1.2437	1.181	1.2545
x_3	.8277	.785	.8358	y_3	.5299	.504	.5365
x_4	.2322	.222	.2355				
x_1	4.2696	4.316		y_1	3.6055	3.605	
x_2	2.9414	2.895		y_2	2.5370	2.499	
x_3	2.1326	2.103		y_3	1.8409	1.821	
x_4	1.5492	1.540		y_4	1.3209	1.317	
x_5	1.0926	1.095		y_5	.9050	.910	
x_6	.7175	.726		y_6	.5582	.566	
x_7	.3990	.407		y_7	.2607	.266	
x_8	.1223	.126					
x_1	5.2635	5.768		y_1	4.6913	5.069	
x_2	4.1192	4.371		y_2	3.7503	3.978	
x_3	3.3814	3.596		y_3	3.1085	3.305	
x_4	2.8357	3.025		y_4	2.6191	2.804	
x_5	2.4025	2.583		y_5	2.2230	2.398	
x_6	2.0435	2.214		y_6	1.8903	2.055	
x_7	1.7370	1.896		y_7	1.6034	1.756	
x_8	1.4697	1.616		y_8	1.3512	1.490	
x_9	1.2327	1.365		y_9	1.1262	1.250	
x_{10}	1.0198	1.136		y_{10}	.9232	1.031	
x_{11}	.8266	.926		y_{11}	.7382	.829	
x_{12}	.6498	.732		y_{12}	.5683	.642	
x_{13}	.4868	.551		y_{13}	.4112	.467	
x_{14}	.3355	.382		y_{14}	.2650	.302	
x_{15}	.1945	.222		y_{15}	.1283	.147	
x_{16}	.0622	.072					

Table B. Decision and Reconstruction Level Locations for 2, 4, 8, 16 and 32 Level Gamma Quantizers

Level	OPT1	P & G	Level	OPT1	P & G
x_1	.5888	.577	y_1	0.0	0.0
x_1	2.2121	2.108	y_1	1.2666	1.205
x_2	.3211	.302			
x_1	3.9979	3.799	y_1	3.0090	2.872
x_2	2.0201	1.944	y_2	1.4557	1.401
x_3	.8913	.859	y_3	.5258	.504
x_4	.1604	.149			
x_1	5.6299	6.085	y_1	4.7177	5.050
x_2	3.8056	4.015	y_2	3.2426	3.407
x_3	2.6797	2.798	y_3	2.2774	2.372
x_4	1.8750	1.945	y_4	1.5670	1.623
x_5	1.2590	1.300	y_5	1.0148	1.045
x_6	.7705	.791	y_6	.5749	.588
x_7	.3792	.386	y_7	.2273	.229
x_8	.0755	.072			
x_1	6.7936	8.043	y_1	6.0794	7.046
x_2	5.3652	6.050	y_2	4.8721	5.444
x_3	4.3791	4.838	y_3	4.0074	4.404
x_4	3.6358	3.970	y_4	3.3388	3.633
x_5	3.0419	3.296	y_5	2.7956	3.022
x_6	2.5493	2.747	y_6	2.3399	2.517
x_7	2.1306	2.287	y_7	1.9494	2.089
x_8	1.7682	1.892	y_8	1.6094	1.720
x_9	1.4505	1.548	y_9	1.3100	1.397
x_{10}	1.1694	1.245	y_{10}	1.0442	1.111
x_{11}	.9190	.976	y_{11}	.8071	.857
x_{12}	.6952	.737	y_{12}	.5953	.630
x_{13}	.4954	.523	y_{13}	.4067	.429
x_{14}	.3179	.334	y_{14}	.2405	.252
x_{15}	.1630	.169	y_{15}	.0988	.101
x_{16}	.0346	.033			

Table C. Decision and Reconstruction Level Locations for 2, 4, 8, 16 and 32 Level Gaussian Quantizers

Level	OPT1	Max	Esteban	Level	OPT1	Max	Esteban
x_1	.7977	.7980	.7984	y_1	0.0	0.0	0.0
x_1	1.5094	1.5100	1.5115	y_1	.9809	.9816	.9927
x_2	.4525	.4528	.4540				
x_1	2.1483	2.152	2.1541	y_1	1.7449	1.748	1.7510
x_2	1.3416	1.344	1.3479	y_2	1.0481	1.050	1.0540
x_3	.7546	.756	.7602	y_3	.4996	.5006	.5039
x_4	.2446	.2451	.2477				
x_1	2.7227	2.733		y_1	2.3921	2.401	
x_2	2.0616	2.069		y_2	1.8366	1.844	
x_3	1.6117	1.618		y_3	1.4312	1.437	
x_4	1.2507	1.256		y_4	1.0943	1.099	
x_5	.9378	.9424		y_5	.7956	.7996	
x_6	.6534	.6568		y_6	.5197	.5224	
x_7	.3860	.3881		y_7	.2568	.2582	
x_8	.1277	.1284					
x_1	3.2269	3.263		y_1	2.9458	2.977	
x_2	2.6647	2.692		y_2	2.4792	2.505	
x_3	2.2937	2.319		y_3	2.1499	2.174	
x_4	2.0060	2.029		y_4	1.8857	1.908	
x_5	1.7655	1.788		y_5	1.6605	1.682	
x_6	1.5554	1.577		y_6	1.4610	1.482	
x_7	1.3666	1.387		y_7	1.2800	1.299	
x_8	1.1934	1.212		y_8	1.1126	1.130	
x_9	1.0319	1.049		y_9	.9556	.9718	
x_{10}	.8794	.8947		y_{10}	.8066	.8210	
x_{11}	.7339	.7473		y_{11}	.6638	.6761	
x_{12}	.5938	.6050		y_{12}	.5258	.5359	
x_{13}	.4578	.4668		y_{13}	.3914	.3991	
x_{14}	.3249	.3314		y_{14}	.2595	.2648	
x_{15}	.1942	.1981		y_{15}	.1294	.1320	
x_{16}	.0646	.0659					

Table A1. Convergence Test MSE and NIT Results

Histogram Type				NLOUT	Uniform MSE	Uniform CTST	Laplacian MSE	Laplacian CTST	Gamma MSE	Gamma CTST
Uniform										
2*	11+	11	11	2	8.3326	16.0	8.3326	16.0	8.3325	16.0
					8.3326	0.0	8.3326	0.0	8.3325	0.0
2	21	30	30	4	2.0832	16.0	4.6275	7387.293	4.8750	7739.305
					2.0832	0.0	2.0832	0.0	2.0832	0.0
2	60	96	95	8	.5208	16.0	3.9574	6991.270	4.2220	7135.200
					.5208	0.0	.5208	0.0	.5207	0.0
2	195	341	341	16	.1302	16.0	3.3514	6583.227	3.4870	6575.730
					.1302	.004	.1302	0.0	.1302	0.0
2	485	700	700	32	.0326	16.0	2.8136	6187.199	2.7840	6007.180
					.0325	.008	.0326	0.207	.0326	.219
Laplacian										
2	11	11	11	2	.49620	16.0	.49620	16.0	.49620	16.0
					.49618	0.0	.49618	0.0	.49618	0.0
8	37	35	36	4	.41619	6184.039	.22704	771.056	.28077	918.7
					.17358	0.0	.17358	0.0	.17358	0.0
17	102	108	110	8	.48868	15535.5	.11489	709.5	.15046	690.0
					.05288	0.0	.05288	0.0	.05286	0.0
75	332	331	338	16	.54714	28688.0	.05709	702.0	.06939	597.0
					.01457	0.0	.01457	0.0	.01457	0.0
225	700	700	700	32	.50698	30736.0	.02804	702.4	.02907	540.0
					.00378	.023	.00378	0.105	.00378	0.129
Gamma										
2				2	.66162	16.0	.66162	16.0	.66162	16.0
					.66063	0.0	.66063	0.0	.66063	0.0
10	37	35	36	4	.47015	5847.0	.29117	874.92	.34994	1039.0
					.22587	0.0	.22587	0.0	.22587	0.0
34	109	101	109	8	.25112	2540.0	.16117	1063.0	.20016	1000.0
					.06648	0.0	.06648	0.0	.06648	0.0
75	308	313	319	16	.33294	16160.0	.09330	1123.0	.10689	1009.0
					.01769	0.0	.01769	0.0	.01769	0.0
200	700	700	700	32	.49867	30736.0	.05474	1164.6	.05309	1011.7
					.00447	.059	.00476	.082	.00448	0.0

* Indicates NIT beyond which no MSE change occurs.

\+ Indicates NIT in which CTST first became 0.0.

Table A2. Convergence Test Results for Optimum Quantized Sentence S1

Histogram Type			NLOUT	Start Sequence Type			
				Uniform		Laplacian	
				MSE	CTST	MSE	CTST
Optimum							
2	11	11	2	1.9997	3168.0	2.2442	16.0
				1.9613	0.0	1.9613	0.0
7	29	27	4	3.1915	2216.0	.69101	2642.0
				.5107	0.0	.51073	0.0
20	67	67	8	2.3110	11996.0	.48002	2827.0
				.1382	0.0	.13821	0.0
100	194	194	16	.71865	24106.0	.36234	2612.0
				.04045	0.0	.04045	0.0
	324	320	32	.08158	3168.0	.26515	2369.0
				.01808	0.0	.02540	0.0
				Gamma		Optimum	
				MSE	CTST	MSE	CTST
	11	11	2	2.2442	16.0	2.2443	16.0
				1.9613	0.0	1.9613	0.0
	37	27	4	.77854	2906.0	.86182	2946.0
				.51073	0.0	.51073	0.0
	68		8	.55269	2860.0	.41260	2860.0
				.13821	0.0	.13805	0.0
	197	196	16	.38483	2561.0	.18210	1221.0
				.04045	0.0	.04045	0.0
	343	339	32	.26419	2202.0	.07762	1067.0
				.02540	0.0	.02540	0.0

Table A3. Uniform Quantizer DMIN and NIT for a Given CTST

NLOUT	CTST	Algorithm DMIN (NIT) Values Uniform		Laplacian		Gamma	
4	10	.00048	(1)	.00024	(10)	.000384	(10)
	1	.00014	(5)	.00024	(14)	.000288	(14)
	.1	.00029	(9)	.000144	(17)	.000096	(17)
	.01	.0	(12)	.0	(21)	.0	(21)
8	100	.000749	(1)	.467	(21)	.5063	(22)
	10	.000077	(2)	.0078	(36)	.00879	(36)
	1	.000518	(12)	.00028	(50)	.000288	(51)
	.1	.000672	(27)	.000077	(65)	.000077	(65)
	.01	.0	(111)	.0	(87)	.0	(86)
16	100			9.0926	(51)	9.103	(52)
	10	.00307	(1)	.104	(110)	.104	(111)
	1	.00046	(13)	.00064	(169)	.00652	(170)
	.1	.00107	(71)	.000998	(229)	.000922	(230)
	.01	.0	(186)	.0	(700)	.0	(700)
32	100			130.25	(70)	134.55	(72)
	10	.018	(1)	1.5405	(298)	1.5339	(301)
	1	.008509	(8)	.02801	(537)	.02346	(541)
	.1	.003993	(151)	.0	(700)	.0	(700)
	.01	.0	(700)	.0		.0	

Table A4. Laplacian Quantizer DMIN and NIT for a Given CTST

NLOUT	CTST	Uniform		Laplacian		Gamma	
		Algorithm DMIN (NIT) Values					
4	100	.4166	(8)	.7028	(5)	.54596	(6)
	10	.00322	(13)	.002247	(11)	.00512	(11)
	1	.000518	(18)	.000173	(15)	.00322	(16)
	.1	.000058	(23)	.0		.0	
	.01	.0					
8	100	2.344	(18)	3.41069	(14)	3.4958	(16)
	10	.038706	(36)	.028685	(33)	.02955	(35)
	1	.000359	(54)	.001305	(51)	.001324	(53)
	.1	.000416	(72)	.000208	(69)	.000227	(71)
	.01	.0		.0		.0	
16	100	22.5164	(23)	43.609	(18)	60.5752	(20)
	10	.175952	(88)	.3866	(85)	.385544	(92)
	1	.002883	(153)	.0152	(153)	.015309	(160)
	.1	.004394	(218)	.00027	(218)	.008513	(223)
	.01	.0		.0	(301)	.0	(308)
32	100	76.2245	(49)	176.55	(17)	264.384	(16)
	10	1.6264	(111)	7.4523	(166)	7.6743	(190)
	1	.09108	(249)	.08525	(423)	.063000	(448)
	.1	.016680	(524)	.0	(700)	.0	(700)
	.01	.0	(700)				

Table A5. Gamma Quantizer DMIN and NIT for a Given CTST

NLOUT	CTST	Algorithm DMIN (NIT) Values: Uniform		Laplacian		Gamma	
4	100	.22234	(8)	.23354	(6)	.16806	(7)
	10	.001505	(13)	.002214	(11)	.00433	(11)
	1	.000044	(18)	.000089	(15)	.000089	(16)
	.1	.0	(22)	.000084	(20)	.0	(21)
	.01	.0	(28)	.0	(26)	.0	(27)
8	100	1.00535	(21)	1.51780	(17)	1.41452	(19)
	10	.023404	(37)	.012289	(35)	.015688	(36)
	1	.001248	(54)	.001609	(52)	.00097	(54)
	.1	.0	(71)	.000090	(69)	.00009	(70)
	.01	.0	(90)	.0	(92)	.0	(90)
16	100	13.276	(38)	24.410	(27)	29.6329	(30)
	10	.18767	(95)	.19948	(92)	.19959	(98)
	1	.01226	(159)	.018267	(155)	.018767	(160)
	.1	.0148	(222)	.013340	(217)	.01074	(222)
	.01	.000509	(309)	.001357	(303)	.001357	(295)
32	100	52.091	(54)	149.440	(27)	214.779	(26)
	10	1.41162	(206)	4.191	(198)	4.23592	(219)
	1	.01028	(431)	.04223	(508)	.04357	(529)
	.1	.03128	(647)	.00178	(687)	.0	(700)
	.01	.03128	(700)	.00178	(700)		

Table A6. Optimum Quantizer DMIN and NIT for a Given CTST

NLOUT	CTST	Algorithm DMIN (NIT) Values Uniform	Laplacian	Gamma	Optimum
4	100	.450 (7)	.2009 (5)	.2541 (5)	.09052 (6)
	10	.0654 (10)	.06483 (8)	.06735 (8)	.03741 (8)
	1	.00636 (13)	.00403 (11)	.00419 (11)	.00532 (11)
	.1	.00063 (16)	.00039 (14)	.00039 (14)	.0 (14)
	.01	.0 (20)	.0 (18)	.0 (18)	.0 (18)
8	100	.6421 (21)	.67764 (19)	.5513 (20)	.42152 (20)
	10	.04587 (39)	.02033 (37)	.02445 (38)	.02735 (38)
	1	.00549 (53)	.00195 (54)	.00398 (54)	.00195 (53)
	.1	.00051 (55)	.00036 (56)	.00080 (56)	.00014 (56)
	.01	.0 (58)	.0 (58)	.0 (59)	.0 (58)
16	100	16.659 (35)	14.016 (40)	22.172 (35)	12.858 (42)
	10	.6985 (110)	.47638 (125)	.45329 (129)	.34445 (125)
	1	.09228 (135)	.00645 (178)	.01814 (181)	.03468 (179)
	.1	.00314 (184)	.00336 (181)	.0025 (184)	.00129 (180)
	.01	.0 (188)	.0 (185)	.0 (188)	.0 (187)
32	100	20.736 (18)	39.752 (44)	45.019 (44)	36.558 (34)
	10	1.6643 (79)	1.5192 (250)	2.1734 (265)	1.5456 (247)
	1	.06974 (101)	.11778 (295)	.1081 (305)	.02043 (300)
	.1	.0123 (213)	.10861 (301)	.10101 (312)	.00358 (306)
	.01	.0 (225)	.00134 (320)	.00165 (333)	.00098 (321)

Table A7. Test Quantizers in which NIT Limit is Imposed

	Number of Bins in Histogram					
Type	128	256	512	1024	2048	4096
UNIFIX						
	31 (.01)					
	63 (.01)	63 (.05)	63 (.01)	63 (.01)	63 (.01)	63 (.01)
	64 (.10)	64 (.10)	64 (.05)	64 (.01)	64 (.01)	64 (.01)
	127 (.10)	127 (.10)	127 (.05)	127 (.01)	127 (.01)	127 (.05)
	128 (.10)	128 (.10)	128 (.05)	128 (.01)	128 (.01)	128 (.05)
	255 (10.)	255 (.05)	255 (.01)	255 (.01)	255 (.01)	255 (.01)
	256 (.50)	256 (.05)	256 (.05)	256 (.01)	256 (.01)	256 (.05)
UNIFLT						
	31 (.10)	31 (.05)	31 (.01)	31 (.01)		
	32 (.10)	32 (.10)	32 (.05)	32 (.01)	32 (.01)	
	63 (.10)	63 (.10)	63 (.05)	63 (.01)	63 (.01)	63 (.01)
	64 (.10)	64 (.10)	64 (.05)	64 (.01)	64 (.01)	64 (.01)
	127 (.10)	127 (.05)	127 (.01)	127 (.01)	127 (.01)	127 (.05)
	128 (.10)	128 (.10)	128 (.05)	128 (.01)	128 (.01)	128 (.05)
	255 (.10)	255 (.05)	255 (.01)	255 (.01)	255 (.01)	255 (.01)
	256 (.10)	256 (.05)	256 (.05)	256 (.01)	256 (.01)	256 (.05)
GAMFIX						
	31 (.01)	31 (.01)	31 (.01)			
	32 (.05)			32 (.01)	32 (.01)	
	63 (1.0)	63 (1.0)	63 (1.0)	63 (1.0)	63 (1.0)	63 (1.0)
	64 (1.0)	64 (1.0)	64 (1.0)	64 (1.0)	64 (1.0)	64 (1.0)
	127 (10.)	127 (1.0)	127 (1.0)	127 (1.0)	127 (1.0)	127 (1.0)
	128 (10.)	128 (1.0)	128 (1.0)	128 (1.0)	128 (1.0)	128 (1.0)
	255 (10.)	255 (10.)	255 (5.0)	255 (1.0)	255 (1.0)	255 (1.0)
	256 (10.)	256 (5.0)	256 (1.0)	256 (1.0)	256 (1.0)	256 (1.0)
GAMFLT						
		31 (.01)				
	32 (.10)	32 (.01)	32 (.01)		32 (.01)	32 (.01)
	63 (.50)	63 (1.0)	63 (1.0)	63 (1.0)	63 (1.0)	63 (1.0)
	64 (.10)	64 (1.0)	64 (1.0)	64 (1.0)	64 (1.0)	64 (1.0)
	127 (1.0)	127 (1.0)	127 (1.0)	127 (1.0)	127 (1.0)	127 (1.0)
	128 (1.0)	128 (1.0)	128 (1.0)	128 (1.0)	128 (1.0)	128 (1.0)
	255 (1.0)	255 (1.0)	255 (1.0)	255 (1.0)	255 (1.0)	255 (1.0)
	256 (1.0)	256 (1.0)	256 (1.0)	256 (1.0)	256 (1.0)	256 (1.0)

Table A8. Sentence and Sentence Error Statistics From SPCHSTAT

SENTENCE	MEAN	VARIANCE	STD DEV	ENERGY	MIN	MAX
S1	-1.604156	$3.301555 \cdot 10^7$	5746	$8.124 \cdot 10^7$	-25695	32047
S2	-3.137098	$0.934460 \cdot 10^7$	3057	$2.295 \cdot 10^7$	-32767	28159
S3	-3.068836	$2.833181 \cdot 10^7$	5323	$6.971 \cdot 10^7$	-24687	28687
S4	-3.283953	$2.883544 \cdot 10^7$	5370	$7.095 \cdot 10^7$	-32767	27455
S5	-5.453889	$2.310326 \cdot 10^7$	4807	$5.684 \cdot 10^7$	-31215	24319
S6	-.415504	$1.625681 \cdot 10^7$	4032	$3.999 \cdot 10^7$	-22287	30287
SE1	-5.517688	$1.548686 \cdot 10^7$	3935	$3.804 \cdot 10^7$	-27743	19375
SE2	-2.529350	$1.337668 \cdot 10^7$	3657	$3.286 \cdot 10^7$	-23503	16399
SE3	13.104790	$1.551288 \cdot 10^7$	3939	$3.810 \cdot 10^7$	-20911	17055
SE4	17.602860	$1.399968 \cdot 10^7$	3742	$3.439 \cdot 10^7$	-19823	24079
SE5	-25.604190	$1.395381 \cdot 10^7$	3735	$3.427 \cdot 10^7$	-21935	20463
SE6	-14.078400	$1.351952 \cdot 10^7$	3677	$3.321 \cdot 10^7$	-21151	22975

Table A9. Sentence and Sentence Error Statistics From STAT1

SENTENCE	MEAN	VARIANCE	STD DEV	VARIANCE1
S1	4.78365	$3.305472 \cdot 10^7$	5749	3.07846
S2	3.45186	$.933899 \cdot 10^7$	3056	.86976
S3	3.86393	$2.836219 \cdot 10^7$	5326	2.64144
S4	3.11523	$2.886760 \cdot 10^7$	5373	2.68850
S5	1.25065	$2.312618 \cdot 10^7$	4809	2.15399
S6	5.28060	$1.627064 \cdot 10^7$	4034	1.51532
SE1	1.43709	$1.547763 \cdot 10^7$	3934	1.44147
SE2	3.91520	$1.336919 \cdot 10^7$	3656	1.24510
SE3	20.36649	$1.550299 \cdot 10^7$	3937	1.44383
SE4	24.30269	$1.399446 \cdot 10^7$	3741	1.30334
SE5	-19.34622	$1.394710 \cdot 10^7$	3735	1.29892
SE6	-7.38001	$1.351572 \cdot 10^7$	3626	1.25875

Table A10. SNR and MSE from Output of PCM Coded Sentence S1

	SNR (dB)				MSE			
NL	UNIFIX	UNIFLT	GAMFIX	GAMFLT	UNIFIX	UNIFLT	GAMFIX	GAMFLT
2	-7.64	-7.64	1.67	2.41	8.33258	8.33258	2.10695	1.90040
3	2.72	2.72	7.02	7.02	3.70304	3.70305	.88389	.88389
4	-1.20	-1.20	7.00	8.04	2.08323	2.08322	.67076	.61733
7	9.80	9.80	12.51	12.51	.68023	.68023	.21401	.21401
8	4.93	4.93	12.42	13.29	.52080	.52080	.18332	.17307
15	15.97	15.97	18.72	18.72	.14815	.14815	.05065	.05065
16	11.19	11.19	18.60	19.22	.13021	.13021	.04668	.04512
31	21.84	21.84	24.85	24.85	.03469	.03469	.01217	.01217
32	17.47	17.48	24.75	25.04	.03256	.03256	.01167	.01146
63	27.80	27.80	30.70	30.70	.00840	.00840	.00303	.00303
64	23.76	23.80	30.73	30.83	.00814	.00815	.00297	.00294
127	33.51	33.51	34.26	34.25	.00207	.00207	.00130	.00129
128	30.17	30.33	34.30	34.30	.00204	.00204	.00128	.00128
255	38.99	38.99	37.25	37.25	.00052	.00052	.00061	.00067
256	36.67	37.02	37.28	37.28	.00052	.00052	.00063	.00067

Table A11. Quantizer SNR Computed from MSE Output of OPT1

	SNR (dB)			
NLOUT	UNIFIX	UNIFLT	GAMFIX	GAMFLT
2	-4.33	-4.33	1.64	2.09
3	-0.81	-0.81	5.41	5.41
4	1.69	1.69	6.61	6.97
7	6.55	6.55	11.57	11.57
8	7.71	7.71	12.25	12.50
15	13.17	13.17	17.83	17.83
16	13.73	13.73	18.19	18.33
31	19.48	19.48	24.03	24.03
32	19.75	19.75	24.21	24.29
63	25.64	25.64	30.06	30.06
64	25.77	25.77	30.15	30.19
127	31.72	31.72	33.74	33.77
128	31.78	31.78	33.81	33.81
255	37.72	37.72	37.02	36.62
256	37.72	37.72	36.88	36.62

TABLE A12. PCM QUANTIZER MEAN SQUARED ERROR

SENTENCE S1

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.663554	.685808	.612076	.583194
4	4.093747	.677377	.592385	.440997
7	.325455	.164149	.170709	.142845
8	1.001339	.194557	.172484	.121776
15	.078671	.040972	.041820	.034751
16	.236203	.052205	.042570	.031500
31	.020336	.010091	.010122	.009115
32	.055693	.012944	.010319	.008537
63	.005174	.002665	.002556	.004647
64	.013079	.003080	.002557	.004645

SENTENCE S2

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	.552648	.345005	.309061	.286837
4	4.793289	.320779	.272928	.227764
7	.236047	.142259	.102633	.080159
8	1.063334	.138017	.094932	.064563
15	.070348	.059149	.031044	.021178
16	.239352	.058648	.029876	.016386
31	.020945	.026899	.010565	.005287
32	.054275	.026888	.010274	.005132
63	.005606	.016007	.005279	.002248
64	.012695	.016058	.005275	.002083

SENTENCE S3

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.361778	.710580	.634026	.628672
4	4.039393	.624599	.537058	.452161
7	.354573	.161380	.148179	.144223
8	.925641	.168963	.140251	.116460
15	.090795	.036980	.039257	.033640
16	.213399	.042397	.038226	.029054
31	.023208	.009934	.009626	.008697
32	.049638	.011324	.009573	.008148
63	.006251	.002571	.002424	.003033
64	.011397	.002801	.002397	.002916

TABLE A13. PCM QUANTIZER MEAN SQUARED ERROR

SENTENCE S4

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.267436	.716740	.596376	.543956
4	4.421296	.687356	.545380	.357406
7	.282989	.166322	.147462	.129244
8	1.045213	.187957	.146139	.108834
15	.071759	.040815	.036691	.035444
16	.244327	.051016	.037319	.029672
31	.019432	.009755	.009326	.009243
32	.057467	.012429	.009520	.008731
63	.005062	.002620	.002429	.003314
64	.013505	.003129	.002462	.003304

SENTENCE S5

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.135821	.662970	.581337	.533445
4	4.280851	.603230	.506281	.413150
7	.309395	.188029	.143468	.122769
8	.982790	.188031	.133078	.104708
15	.082774	.044196	.033352	.032330
16	.226251	.048121	.032658	.026119
31	.022231	.009766	.008275	.008874
32	.052491	.011209	.008345	.007316
63	.005790	.002626	.002187	.003391
64	.012367	.002907	.002194	.003376

SENTENCE S6

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	.928784	.477261	.414794	.368882
4	4.556890	.458982	.376753	.283065
7	.280035	.143936	.108506	.087794
8	1.054601	.149142	.100972	.073137
15	.067596	.037796	.024750	.021865
16	.248956	.041058	.024681	.019843
31	.018779	.009679	.006414	.006260
32	.057335	.010815	.006461	.006080
63	.005203	.003203	.001595	.002432
64	.013261	.003392	.001599	.002426

TABLE A14. PCM SIGNAL TO NOISE RATIO (DB)

SENTENCE S1

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.719660	6.568570	7.062600	7.273350
4	-1.202870	6.624000	7.205930	8.486630
7	9.801870	12.777220	12.604550	13.381370
8	4.927690	12.029980	12.560110	14.075380
15	15.971100	18.804030	18.714900	19.521840
16	11.186080	17.755200	18.640090	19.948060
31	21.841320	24.889910	24.876460	25.332460
32	17.473020	23.799100	24.792650	25.617250
63	27.790220	30.672490	30.854350	28.259320
64	23.757220	30.042660	30.853150	28.261730

SENTENCE S2

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.017540	4.064540	4.540420	4.858830
4	-7.371570	4.374550	5.073060	5.846010
7	5.701500	7.909970	9.327660	10.401870
8	-.824460	8.041320	9.667130	11.342590
15	10.968750	11.722300	14.523810	16.182980
16	5.641100	11.759100	14.689350	17.278560
31	16.226670	15.146630	19.198380	22.209110
32	12.093260	15.152380	19.322750	22.337200
63	21.953860	17.383850	22.215410	25.924650
64	18.402020	17.360820	22.218460	26.254910

SENTENCE S3

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.920770	5.746120	6.241810	6.279930
4	-1.812300	6.307530	6.963800	7.709600
7	8.761480	12.182740	12.553250	12.671450
8	4.600160	11.983800	12.793240	13.600970
15	14.680250	18.582570	18.323560	18.995670
16	10.960010	17.990050	18.442090	19.630250
31	20.600280	24.289170	24.426470	24.868590
32	17.304890	23.716890	24.450780	25.151810
63	26.300960	30.158660	30.417010	29.442730
64	23.689320	29.789140	30.467930	29.613820

TABLE A15. PCM SIGNAL TO NOISE RATIO (DB)

SENTENCE S4

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	3.312700	5.789620	6.587820	6.987430
4	-2.123720	5.971640	6.978160	8.807780
7	9.818530	12.131700	12.654420	13.227650
8	4.153060	11.592000	12.694790	13.973190
15	15.782040	18.234180	18.695450	18.848270
16	10.452170	17.268170	18.622830	19.618010
31	21.451030	24.448970	24.644060	24.684250
32	16.746920	23.387150	24.555920	24.931140
63	27.296970	30.158130	30.487300	29.139680
64	23.034130	29.388670	30.431530	29.152660

SENTENCE S5

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.825630	5.165680	5.735970	6.110250
4	-2.947270	5.580240	6.334940	7.224440
7	8.467690	10.629190	11.810800	12.488500
8	3.457160	10.629030	12.139990	13.180050
15	14.198850	16.926010	18.148440	18.282090
16	9.825660	16.556500	18.239760	19.210220
31	19.904590	23.481060	24.200390	23.897290
32	16.177120	22.882480	24.164440	24.735640
63	25.750900	29.186220	29.981890	28.074510
64	22.454240	28.741700	29.970470	28.095210

SENTENCE S6

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.172930	5.066660	5.675500	6.183070
4	-4.742120	5.237280	6.088900	7.338730
7	7.374480	10.269550	11.496740	12.418220
8	1.623440	10.116610	11.811900	13.212550
15	13.551520	16.078080	17.915190	18.450210
16	7.881020	15.721890	17.927440	18.874400
31	19.107790	21.992200	23.779390	23.886870
32	14.265090	21.509720	23.750240	24.013030
63	24.687810	26.796190	29.822920	27.993390
64	20.623490	26.551910	29.823320	28.004150

TABLE A16. ADPCM SIGNAL TO NOISE RATIO (DB)

SENTENCE S1

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.54304	11.46650	11.32050	11.37110
4	4.39639	14.09050	12.49080	13.53940
7	9.68309	18.43080	16.89700	19.32030
8	10.63210	19.27451	17.84621	20.24860
15	16.09779	24.36591	23.21790	25.44341
16	16.71651	24.87030	23.63470	25.76050
31	22.47200	30.49719	29.32140	31.38319
32	22.67371	30.77010	29.55350	31.61659
63	28.57091	36.65849	35.73599	36.60471
64	28.76230	36.73289	35.90421	36.77229

SENTENCE S2

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.67648	6.85073	7.74859	6.96054
4	1.39156	9.44976	10.02370	8.94076
7	7.36612	15.02450	14.41010	14.68830
8	7.54702	16.21460	15.33480	15.68050
15	13.16270	21.14740	20.49010	21.23511
16	13.69510	21.92900	20.93291	22.01930
31	19.30389	27.24249	26.60670	27.24300
32	19.70461	27.50060	26.84489	27.61189
63	25.51601	33.29559	32.85170	31.59171
64	25.76880	33.40910	33.02310	31.59790

SENTENCE S3

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.79844	10.34700	10.98550	10.45500
4	4.40110	13.56910	12.57380	12.72430
7	9.77199	18.72079	16.82750	19.27390
8	10.62540	19.50391	17.77890	20.17599
15	16.14931	24.35770	23.39050	25.04710
16	16.71429	24.90930	23.75951	25.99730
31	22.43050	30.43030	29.47749	31.58040
32	22.77020	30.87489	29.65781	31.94769
63	28.66090	36.76970	35.68089	37.16541
64	28.78580	36.90050	35.68269	37.22279

TABLE A17. ADPCM SIGNAL TO NOISE RATIO (DB)

SENTENCE S4

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	3.35663	11.81780	12.30360	11.77260
4	5.02210	15.00160	13.45990	14.25440
7	10.22880	19.23950	17.70129	20.27370
8	11.43860	20.28529	18.65390	21.35420
15	16.75391	25.50101	24.08380	26.09250
16	17.36349	26.01900	24.39861	26.85460
31	23.16350	31.49989	30.35320	32.36940
32	23.44370	31.77431	30.56889	32.60660
63	29.24989	37.50310	36.44640	36.92419
64	29.51260	37.90630	36.65630	36.90810

SENTENCE S5

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.96691	8.85372	10.42280	9.42383
4	4.24156	12.30440	12.44670	12.12840
7	9.42909	18.11330	17.13499	18.17059
8	10.33440	19.02921	17.76691	19.12981
15	16.01030	24.31731	23.12579	24.25810
16	16.61690	24.79359	23.67970	25.17380
31	22.28819	30.46539	29.37691	30.63860
32	22.55170	30.62830	29.73759	30.73129
63	28.41560	36.34590	35.65550	34.22650
64	28.60860	36.45490	35.73460	35.10210

SENTENCE S6

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	2.52810	9.90422	10.62820	10.28060
4	4.15094	12.90780	12.45920	12.25720
7	9.43763	17.91750	17.23540	18.30000
8	10.33590	18.99159	17.89700	19.10539
15	15.89240	24.04581	23.35110	24.77859
16	16.39619	24.65060	23.54601	25.23289
31	22.15720	30.10519	29.47400	30.52730
32	22.40359	30.26440	29.67650	30.82950
63	28.37770	36.20869	35.59900	35.37480
64	28.39430	36.33701	35.61929	35.38010

TABLE A18. ADPCM QUANTIZER MEAN SQUARED ERROR

SENTENCE S1

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.399247	.286833	.370911	.277151
4	3.167400	.215057	.304215	.186910
7	.574423	.082773	.107382	.069357
8	.637734	.072665	.094152	.056071
15	.134853	.020902	.026377	.017895
16	.152986	.020729	.025452	.015799
31	.031677	.005152	.006587	.005000
32	.038380	.005506	.006548	.004823
63	.007493	.001328	.001519	.001502
64	.009644	.001396	.001508	.001472

SENTENCE S2

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.064790	.322781	.344429	.311524
4	3.757558	.252746	.271948	.194018
7	.461849	.081563	.088935	.072376
8	.758929	.074612	.079372	.060852
15	.116611	.019657	.022801	.018899
16	.176066	.019977	.022008	.015396
31	.029076	.004898	.005666	.004725
32	.042396	.005370	.005690	.004380
63	.007089	.001197	.001326	.001927
64	.010582	.001336	.001339	.001900

SENTENCE S3

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.401379	.294516	.394108	.277046
4	3.069333	.215839	.316433	.187064
7	.610309	.080429	.111096	.068184
8	.589275	.070822	.096703	.055376
15	.140145	.020842	.026893	.018000
16	.143847	.020269	.025373	.015060
31	.032572	.005070	.006697	.004292
32	.036658	.005190	.006530	.003987
63	.007757	.001252	.001560	.001279
64	.009218	.001296	.001541	.001256

TABLE A19. ADPCM QUANTIZER MEAN SQUARED ERROR

SENTENCE S4

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.269851	.247427	.318719	.243908
4	3.384336	.209725	.285405	.166919
7	.556156	.070233	.092299	.060181
8	.702073	.069235	.085794	.049927
15	.121677	.017945	.023395	.015954
16	.174943	.019543	.022472	.013696
31	.028501	.004482	.005650	.004023
32	.044025	.005077	.005626	.003790
63	.006870	.001099	.001354	.001701
64	.010997	.001271	.001365	.001700

SENTENCE S5

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.202139	.299639	.335142	.294604
4	3.542429	.220128	.258939	.188276
7	.486809	.075708	.090716	.069752
8	.722499	.070285	.082884	.058532
15	.128298	.018491	.023319	.018215
16	.166410	.019468	.022622	.015511
31	.029249	.004575	.005785	.004599
32	.042334	.005074	.005802	.004384
63	.007063	.001172	.001384	.002060
64	.010572	.001295	.001396	.001738

SENTENCE S6

LEVELS	UNIFORM	LAPLACIAN	GAMMA	OPTIMUM
3	1.165314	.283000	.323556	.278341
4	3.611168	.226756	.264754	.202280
7	.492417	.073467	.089584	.068245
8	.741471	.069080	.080957	.056692
15	.118666	.018323	.022353	.016757
16	.177511	.019714	.021680	.014863
31	.028693	.004573	.005519	.004376
32	.043575	.005164	.005543	.004006
63	.006827	.001134	.001330	.001443
64	.010952	.001285	.001337	.001437

Table A20. SNR From PCM Coded File S1 as a Function of Number of Output Levels and Number of Histogram Bins

	Number of Bins in Histogram											
	Uniform Quantizer						Gamma Quantizer					
NLOUT	128	256	512	1024	2048	4096	128	256	512	1024	2048	4096
2	-7.56	-7.60	-7.62	-7.63	-7.63	-7.64	1.62	1.65	1.66	1.67	1.67	1.67
3	2.76	2.74	2.73	2.72	2.72	2.72	7.03	7.02	7.02	7.02	7.02	7.02
4	-1.12	-1.17	-1.19	-1.20	-1.20	-1.20	6.81	6.89	6.93	6.96	6.99	7.00
7	9.88	9.84	9.82	9.81	9.80	9.80	12.54	12.51	12.51	12.51	12.51	12.51
8	5.00	4.96	4.94	4.93	4.93	4.93	12.18	12.28	12.34	12.38	12.40	12.42
15	16.04	16.00	15.98	15.97	15.97	15.97	18.74	18.73	18.72	18.72	18.72	18.72
16	11.26	11.22	11.20	11.19	11.18	11.19	18.25	18.40	18.49	18.54	18.58	18.60
31	21.89	21.86	21.85	21.84	21.84	21.84	24.90	24.86	24.86	24.85	24.85	24.85
32	17.55	17.51	17.48	17.47	17.47	17.47	24.24	24.47	24.60	24.67	24.72	24.75
63	27.84	27.81	27.79	27.78	27.79	27.80	28.84	30.75	30.72	30.71	30.70	30.70
64	23.80	23.76	23.75	23.74	23.76	23.76	28.34	30.62	30.62	30.68	30.71	30.73
127	33.51	33.50	33.50	33.49	33.49	33.51	30.88	33.06	34.96	34.47	34.33	34.26
128	30.01	30.12	30.14	30.15	30.15	30.17	31.11	34.20	35.11	34.50	34.36	34.30
255	30.43	39.01	38.94	38.96	38.98	38.99	32.99	35.69	39.02	38.86	37.46	37.25
256	30.17	36.52	36.62	36.65	36.67	36.67	32.96	36.81	39.43	38.95	37.48	37.28

Table A21. SNR From PCM Coded File S1 as a Function of Number of Output Levels and Number of Histogram Bins

Number of Bins in Histogram

	Uniform Quantizer						Gamma Quantizer					
NLOUT	128	256	512	1024	2048	4096	128	256	512	1024	2048	4096
2	-4.33	-4.33	-4.33	-4.33	-4.33	-4.33	1.56	1.61	1.63	1.64	1.64	1.64
3	-0.83	-0.81	-0.81	-0.81	-0.81	-0.81	5.36	5.40	5.41	5.41	5.41	5.41
4	1.65	1.68	1.69	1.69	1.69	1.69	6.43	6.55	6.60	6.61	6.61	6.61
7	6.42	6.52	6.55	6.55	6.55	6.55	11.26	11.50	11.56	11.57	11.57	11.57
8	7.55	7.67	7.70	7.71	7.71	7.71	11.74	12.10	12.21	12.24	12.24	12.25
15	12.59	13.04	13.14	13.17	13.17	13.17	16.43	17.48	17.76	17.82	17.83	17.83
16	13.09	13.58	13.70	13.73	13.73	13.73	16.59	17.73	18.07	18.16	18.18	18.19
31	17.36	18.89	19.35	19.46	19.48	19.48	19.44	22.62	23.71	23.98	24.02	24.02
32	17.58	19.16	19.63	19.74	19.75	19.75	19.77	22.72	23.84	24.14	24.20	24.21
63	20.08	23.62	25.15	25.55	25.63	25.63	20.65	25.79	28.81	29.87	30.06	30.06
64	20.10	23.70	25.27	25.69	25.77	25.77	20.60	25.84	28.94	29.94	30.15	30.15
127	21.07	26.36	30.00	31.41	31.71	31.71	20.93	26.80	31.66	33.67	33.80	33.76
128	21.06	26.42	30.06	31.49	31.78	31.78	20.96	26.88	31.88	33.84	33.82	33.80
255	20.72	27.49	32.93	36.61	37.72	37.73	21 07	26.89	32.97	37.14	37.30	37.01
256	20.77	27.49	32.99	36.57	37.71	37.76	21.12	26.97	33.11	37.36	37.30	36.90

APPENDIX F

PROGRAM LISTINGS

Program listings for the optimum quantizer calculations, PCM speech coder simulations and ADPCM speech coder simulations are given in this section. All programs were developed using the Data General FORTRAN 5 compiler.

OPT1

```
C     PROGRAM OPT1
C     OPTIMUM (MAX) QUANTIZER CALCULATION ROUTINE.  CAN RUN MANY
C         QUANTIZERS AT ONE TIME, OR A SINGLE QUANTIZER.  MANY
C         OPTIONS ARE AVAILABLE.  OUTPUTS INCLUDE SNR,
C         QUANTIZED SPEECH, QUANTIZATION ERROR, AND
C         QUANTIZER MSE.
C     AUTHOR:    CHAS GIMARC
C     EXECUTION FORMAT:   OPT1    F1/D  (F2/I)  (F3/E)  (F4/O)  (F5/L)
C                                 (F6/Q)  (F7/S)  (F8/P)
C     LOCAL SWITCHES:     /D     RUN TIME ASCII DATA FILE.  CONTAINS DATA
C                                IOFF,NSPL,NBLK,VAR,RNVAR,INPT,ITYP,NNBIN
C                         /I     INPUT BINARY SPEECH-TO-BE-QUANTIZED FILE
C                         /E     OUTPUT QUANTIZATION ERROR FILE
C                         /O     OUTPUT QUANTIZED SPEECH FILE
C                         /L     OUTPUT ONE LINE LISTING PRINT FILE
C                         /Q     OUTPUT REAL ASCII QUANTIZER PARAMETER
C                                FILE (APPEND)
C                         /S     OUTPUT SUMMARY SHEET FOR EACH QUANTIZER
C                                (APPEND)
C                         /P     SRT START LEVEL ASCII FILE
C                         /G     GRAPH OF QUANTIZER OUTPUT FILE
C
C
C*********************************************************************
C
C
      COMPILER FREE
      INTEGER IP(4097),IPP(4097),IIN1(515),NOBINS(12),IPST(4097)
      INTEGER IA1(3),IA2(3),IDEC(257),NRLEV(32),ITER(32,11)
      REAL DEC(257),DECLA(257),DECP(257),REC(256),CTT(11),TIM(32,11)
      REAL SNOIS(32,11),MSER(32,11)
      COMMON/01/ITEST(9),ICHAN(9),ILET(2,9)
      EQUIVALENCE (ITEST(1),IDAT),(ITEST(2),ISPCH),(ITEST(3),IQERR)
      EQUIVALENCE (ITEST(4),IQOUT),(ITEST(5),ILST),(ITEST(6),IQLEV)
      EQUIVALENCE (ITEST(7),ISMST),(ITEST(8),IPNT),(ITEST(9),IGPH)
      EQUIVALENCE (IIN1(4),IDEC(1))
      DATA ITEST/9*0/,ICHAN/1,2,3,4,-20,21,-22,23,24/
      DATA ILET/10000K,0,200K,0,4000K,0,2,0,20K,0,0,100000K,0
     1        ,20000K,1,0,1000K,0/
      CALL OPNALL (9,ITEST,ICHAN,ILET)
      IF (IDAT.EQ.0) STOP "DATA FILE MISSING FROM OPT1"
      READ (IDAT) IOFF,NSPL,VAR,RNVAR,INPT,ITYP,NNBIN,NNLOUT,NCTST
     1,NITYP
      READ (IDAT) (NOBINS(J),J=1,NNBIN)
      READ (IDAT) (CTT(J),J=1,NCTST)
      READ (IDAT) (NRLEV(J),J=1,NNLOUT)
      NMSEBN = 4096
```

```
      IHEAD = 0
      NBLK = NSPL/256
      NSTBK = IOFF/256
      SDEV = SQRT(VAR)
      IF (ITYP.GE.7) GO TO 10
      IF (RNVAR.EQ.10..OR.RNVAR*SDEV.GT.32768.) RNVAR = 32768./SDEV
      XMIN = -RNVAR * SDEV
      XMAX = RNVAR * SDEV
      CALL THTSB (NMSEBN,SDEV,ITYP,IPP)
      GO TO 20
   10 INC = 1
      CALL STATSSB (IOFF,NSPL,INC,NMSEBN,ISPCH,DMIN,DMAX,IPP)
   20 DO 250 JGO=1,NNBIN
      NBIN = NOBINS(JGO)
      IF (ITYP.GE.7) GO TO 30
      CALL THTSB (NBIN,SDEV,ITYP,IP)
      IF (NITYP.NE.ITYP) CALL THTSB (NBIN,SDEV,NITYP,IPST)
      GO TO 40
   30 CALL STATSSB (IOFF,NSPL,INC,NBIN,ISPCH,DMIN,DMAX,IP)
      XMIN = DMIN
      XMAX = DMAX
   40 DO 210 JMIN=1,NNLOUT
      NLOUT = NRLEV(JMIN)
      IF (NITYP.NE.ITYP) GO TO 42
      CALL SRTSB (IP,IIN1,XMIN,XMAX,ITYP,NBIN,NLOUT,IPNT)
      GO TO 43
   42 CALL SRTSB (IPST,IIN1,XMIN,XMAX,NITYP,NBIN,NLOUT,IPNT)
   43 CONTINUE
      DO 200 JMAX=1,NCTST
      CTEST = CTT(JMAX)
C
C
C     OPTIMUM QUANTIZER CALCULATION LOOP
C
C
      RITIM = 0.
      IOT = 1
      NT = NLOUT +  1
      TYPE XMIN,XMAX,ITYP,NBIN,NLOUT,INPT
      MID = NLOUT/2 + 1
      IEVN = 0
      IF (NLOUT/2. - NLOUT/2 .GT.0.1) IEVN = 1
      CALL TIME (IA1,IER)
      DEL = (65536.)/NBIN
      DELT = (65536.)/4096.
      DO 50 J=1,NT
      DECLA(J) = FLOAT(IDEC(J))
   50 DEC(J) = DEL*(IDEC(J) - 1) - 32768.
      NIT = 0
   60 CALL QUAN (DEC,DECP,DECLA,REC,IP,DEL,NIT,NLOUT,MID,IEVN,INPT)
      CALL QUANER (DEC,DECP,NT,CTEST,ICT)
```

```
      CALL MSE (DECLA,IPP,REC,DELT,NLOUT,SM2)
   65 IF (NIT.GE.1000) GO TO 70
      IF (ICT.GE.1)  GO TO 60
   70 CALL TIME (IA2,IER)
   80 ITIM = (IA2(1)-IA1(1))*3600 + (IA2(2)-IA1(2))*60 + IA2(3)-IA1(3)
      RITIM = ITIM + RITIM
      IF (RITIM.LE.1) GO TO 100
   90 CALL MSE (DECLA,IPP,REC,DELT,NLOUT,SM2)
      IF (IQLEV.EQ.0) GO TO 150
   91 DO 92 J=2,NLOUT
      ADEC = DEC(J)
   92 WRITE (IQLEV) ADEC
      DO 94 J=1,NLOUT
      AREC = REC(J)
   94 WRITE (IQLEV) AREC
      GO TO 150
  100 IOT = 10
      ITIM = 0
      DO 130 LM=1,IOT
      CALL TIME (IA1,IER)
      DO 110 J=1,NT
      DECLA(J) = FLOAT(IDEC(J))
  110 DEC(J) = DEL*(IDEC(J) - 1) - 32768.
      NIT = 0
  120 CALL QUAN (DEC,DECP,DECLA,REC,IP,DEL,NIT,NLOUT,MID,IEVN,INPT)
      CALL QUANER (DEC,DECP,NT,CTEST,ICT)
      IF  (ICT.GE.1) GO TO 120
      CALL TIME  (IA2,IER)
  130 ITIM = (IA2(1)-IA1(1))*3600 + (IA2(2)-IA1(2))*60 + IA2(3)-IA1(3)
     1        + ITIM
      RITIM = ITIM/FLOAT(IOT)
      GO TO 90
  150 CALL QNTIZESB (DEC,REC,NLOUT,XMIN,XMAX,NBLK,NSTBK,ISPCH,
     1                 IQOUT,IQERR,SNR,RMSE)
      IF (ISMST.NE.0)  CALL SUMMRYSB (DEC,REC,NSPL,NBIN,NLOUT,NBLK,
     1    SDEV,RNVAR,XMIN,XMAX,ITYP,CTEST,NIT,SM2,RITIM,SNR,ISMST)
      TIM(JMIN,JMAX) = RITIM
      ITER(JMIN,JMAX) = NIT
      MSER(JMIN,JMAX) = SM2
  200 SNOIS(JMIN,JMAX) = SNR
      IF (IGPH.EQ.0) GO TO 210
      WRITE (IGPH) NLOUT,SDEV,SNR
      DO 201  J=1,NT
  201 WRITE (IGPH) DEC(J)
      DO 202 J=1,NLOUT
  202 WRITE (IGPH) REC(J)
  210 CONTINUE
      IF (ILST.EQ.0) GO TO 220
      IF (IHEAD.NE.0) GO TO 215
      WRITE (ILST,300)
  215 DO 217  ILCT=1,NNLOUT
```

```
      DO 216  ICT2=1,NCTST
  216 WRITE (ILST,310) RMSE,NBIN,NRLEV(ILCT),XMIN,XMAX,CTT(ICT2),
     1                 ITER(ILCT,ICT2),TIM(ILCT,ICT2),MSER(ILCT,ICT2),
     2                 SNOIS(ILCT,ICT2)
  217 CONTINUE
  220 IHEAD = 1
  250 CONTINUE
  300 FORMAT (///5X,"OPTIMUM QUANTIZER SUMMARY SHEET"///"  START   SPL",
     1        " BINS LEV   MIN      MAX    LIMIT NIT  TIME     MSE    ",
     2        "    SNR"//)
  310 FORMAT (1X,F11.6,1X,I4,1X,I3,F9.2,1X,F8.2,1X,E6.1,1X,I4,1X,
     1        F6.1,1X,F8.6,1X,F10.5)
      CALL FBACK
      END
```

MSE

```
C     SUBROUTINE MSE
C     ROUTINE CALCULATES THE MEAN SQUARED ERROR OF A QUANTIZER.
C          CALCULATION IS BASED UPON GIVEN DECISION LEVEL (DECLA) AND
C          RECONSTRUCTION LEVEL (REC) INPUTS, AND A PDF HISTOGRAM (IP).
C          ROUTINE RETURNS SM2 WHICH IS THE MSE
C     AUTHOR:  CHAS GIMARC
C     EXECUTION FORMAT:    MSE (DECLA,IP,REC,DEL,NLOUT,SM2)
C
C
C***********************************************************************
C
C
      SUBROUTINE MSE (DECLA,IP,REC,DEL,NLOUT,SM2)
      REAL DECLA(257),REC(256),DECL(257)
      INTEGER IP(4097)
      SM1 = 0.0
      SM2 = 0.0
      SM3 = 0.0
      RK = 4096./(DECLA(NLOUT+1)-1)
      DO 30 J=2,NLOUT
   30 DECL(J) = DECLA(J)*RK
      DECL(NLOUT+1) = 4097.
      DECL(1) = 1
      DO 20 K=1,NLOUT
      L1 = IFIX(DECL(K))
      L2 = IFIX(DECL(K+1) - 1)
      DO 10 J = L1,L2
      SM3 = SM3 + IP(J)
   10 SM1 = SM1 + IP(J)*((DEL*(J-.5)-32768.) - REC(K))**2
      SM2 = SM1 + SM2
   20 SM1 = 0.0
      SM2 = SM2/SM3/(3276.8**2)
      RETURN
      END
```

QNTIZESB

```
C       SUBROUTINE QNTIZESB
C       PROGRAM QUANTIZES A CONTIGUOUS FILE (SPEECH) ACCORDING TO THE
C            DECISION LEVELS AND RECONSTRUCTION LEVELS INPUT TO THE
C            PROGRAM.  OUTPUT CONSISTS OF THE QUANTIZED INPUT AND THE
C            QUANTIZATION ERROR FOR EACH SAMPLE.  TO BE RUN WITH OPT1
C       AUTHOR:    CHAS GIMARC
C       EXECUTION FORMAT:    QNTIZESB (DEC,REC,NLOUT,XMIN,XMAX,NBLK,NSTBK
C                                    ,ISN,IST,IER,SNR)
C
C
C***********************************************************************
C
C
        SUBROUTINE QNTIZESB (DEC,REC,NLOUT,XMIN,XMAX,NBLK,NSTBK,ISN,IST,
       1                      IER,SNR,RMSE)
        COMPILER FREE
        INTEGER ISIN(256),ISOUT(256),IQER(256)
        REAL DEC(257),REC(256),NVAR
        NTM1 = NLOUT - 1
        NTP1 = NLOUT + 1
        DEC(1) = XMIN
        DEC(NTP1) = XMAX
        SVAR = 0.
        RMSE = 0.
        NVAR = 0.
        COT = 0.
        NBKM1 = NBLK + NSTBK - 1
        NKP1 = NSTBK + 1
        DO 60 NBK = NKP1,NBKM1
        INBK = NBK - 1
        CALL RDBLK (ISN,INBK,ISIN,1,IERR)
        DO 50 M=1,256
        SIG = ISIN(M)
        DO 30 N=1,NLOUT
     30 IF (SIG.GE.DEC(N).AND.SIG.LE.DEC(N+1)) GO TO 40
        IF (SIG.LT.DEC(1)) ISOUT(M) = REC(1)
        IF (SIG.GT.DEC(NLOUT+1)) ISOUT(M) = REC(NLOUT)
        GO TO 41
     40 ISOUT(M) = REC(N)
     41 IQER(M) = ISOUT(M) - ISIN(M)
        IF (ABS(ISIN(M)).GT.32767) TYPE ISIN(M)
        SVAR = SVAR + FLOAT(ISIN(M))**2
        RMSE = (FLOAT(IQER(M)/3276.8)**2) + RMSE
        COT = COT + 1
     50 NVAR = NVAR + FLOAT(IQER(M))**2
        IF (IST.NE.0) CALL WRBLK (IST,INBK,ISOUT,1,IERR)
     60 IF (IER.NE.0) CALL WRBLK (IER,NBLK,IQER,1,IERR)
```

```
SNR = 10.*ALOG10(SVAR/NVAR)
RMSE = RMSE/COT
TYPE "SNR = ",SNR,"      MSE =",RMSE
RETURN
END
```

QUAN

```
C      SUBROUTINE QUAN
C      OPTIMUM QUANTIZER ITERATION ROUTINE.  CALCULATES NEW DECISION
C           LEVELS (DECLA) AND RECONSTRUCTION LEVELS (REC) BASED UPON
C           PAST LEVELS AND A HISTOGRAM (IP).  ROUTINE INCREMENTS
C           NIT EACH TIME IT IS CALLED
C      AUTHOR:  CHAS GIMARC
C      EXECUTION FORMAT:    QUAN (DEC,DECP,DECLA,REC,IP,DEL,NIT,NLOUT,
C                                 MIDNLT,IEVN,INPT)
C
C
C*******************************************************************
C
C
       SUBROUTINE QUAN (DEC,DECP,DECLA,REC,IP,DEL,NIT,NLOUT
      1                 ,MIDNLT,IEVN,INPT)
       REAL DEC(257),DECLA(257),REC(256)
       REAL DECP(257)
       INTEGER IP(4097)
       SM1 = 0.0
       SM2 = 0.0
       NIT = NIT + 1
       DO 20 K = 1,NLOUT
       L1 = IFIX(DECLA(K))
       L2 = IFIX(DECLA(K+1) - 1)
       DO 10 J = L1,L2
       SM1 = SM1 + IP(J)*(DEL*(J-.5)-32768.)
    10 SM2 = SM2 + IP(J)
       SDIF = DECLA(K) - IFIX(DECLA(K))
       DIF = DECLA(K+1) - IFIX(DECLA(K+1))
       WPRO = DIF * IP(L2 + 1)
       SWPRO = SDIF * IP(L1)
       AWPRO = WPRO*(DEL*(L2+DIF/2) - 32768.)
       ASWPRO = SWPRO*(DEL*(L1-1+SDIF/2) - 32768.)
       SM1 = SM1 + AWPRO - ASWPRO
       SM2 = SM2 + WPRO - SWPRO
       REC(K) = SM1/SM2
       IF (INPT.EQ.1.AND.MIDNLT.EQ.K.AND.IEVN.EQ.1) REC(K) = 0.
       SM1 = 0.0
    20 SM2 = 0.0
       DO 30 J=2,NLOUT
       DECP(J) = DEC(J)
       DEC(J) = 0.5*(REC(J) + REC(J-1))
       IF (INPT.EQ.1.AND.MIDNLT.EQ.J.AND.IEVN.EQ.0) DEC(J) = 0.
    30 DECLA(J) = (DEC(J) + 32768.)/DEL + 1
       NT = NLOUT + 1
       DECP(1) = DEC(1)
       DECP(NT) = DEC(NT)
```

```
RETURN
END
```

QUANER

```
C     SUBROUTINE QUANER
C     ERROR TEST ROUTINE TO DETERMINE STOP POINT OF CALCULATION
C           BASED ON A GIVEN CTEST VALUE.  ROUTINE RETURNS A COUNT
C           (ICT) WHICH IS 0 IF NO ERROR IS DETECTED.
C     AUTHOR:  CHAS GIMARC
C     EXECUTION FORMAT:    QUANER (DEC,DECP,NT,CTEST,DEL,XMIN,ICT)
C
C
C*******************************************************************
C
C
      SUBROUTINE QUANER (DEC,DECP,NT,CTEST,ICT)
      REAL DEC(257),DECP(257)
      ICT = 0
      DO 10 J=1,NT
   10 IF (ABS(DEC(J) - DECP(J)).GT.CTEST) ICT = ICT + 1
      RETURN
      END
```

SRTSB

```
C     SUBROUTINE SRTSB
C     CALCULATES DECISION LEVEL INITIAL LOCATIONS BASED UPON EQUAL
C         AREA OF THE INPUT PROBABILITY DENSITY FUNCTION OR
C         HISTOGRAM.  TO BE RUN WITH OPT1.
C     NOTICE:  THIS PROGRAM ALLOWS FOR A QUANTIZER OF UP TO 64 LEVELS
C     AUTHOR:  CHAS GIMARC
C
C
C**************************************************************
C
C
      SUBROUTINE SRTSB (ICBIN,IIN1,XMIN,XMAX,ITYP,NBIN,NLOUT,IPNT)
      INTEGER ICBIN(4097),IIN1(515)
      REAL OLIM(256),F(515)
      EQUIVALENCE (F(2),OLIM(1))
      NCT = 0
      TOT = 0.0
      CNT = 0.0
      LEV = 2
      NB = NBIN + 1
      I1 = IFIX((XMIN + 32768.)*NBIN/65536.) + 1
      I2 = IFIX((XMAX + 32768.)*NBIN/65536.) + 1
      IF (I1.GT.NBIN) I1 = NBIN
      IF (I2.GT.NBIN) I2 = NBIN
      DO 20 I=I1,I2
   20 TOT = TOT + ICBIN(I)
      RMAXCT = TOT/NLOUT
      RMAX2 = RMAXCT*0.5
      XDEL = 65536./NBIN
      DO 30 I=I1,I2
      CNT = CNT + ICBIN(I)
      IF (CNT.LT.RMAX2 + RMAXCT*(LEV-2)) GO TO 30
      NCT = NCT + 1
      IF (NCT.LE.1) F(LEV+NLOUT+1) = - 32768. + XDEL*(I-1)
      IF (CNT.LT.RMAXCT*(LEV-1)) GO TO 30
      OLIM(LEV) = (I-1)*XDEL - 32768.
      LEV = LEV+1
      NCT = 0
   30 CONTINUE
      OLIM(1) = XMIN
      OLIM(NLOUT+1) = XMAX
      F(1) = FLOAT(NLOUT)
      I = 2
      DO 40 J=1,NB
   50 IF (F(I).GT.(J-1)*XDEL - 32768.) GO TO 40
      IIN1(I+2) = J
      I = I + 1
```

```
      IF (I.LE.NLOUT+2) GO TO 50
      GO TO 55
   40 CONTINUE
   55 IIN1(1) = NLOUT
      IIN1(2) = IFIX(XMIN)
      IIN1(3) = IFIX(XMAX)
      IF (IPNT.EQ.0) GO TO 110
      WRITE (IPNT,100) F(1),ITYP
      M = NLOUT + 2
      WRITE (IPNT,120) (I-1,F(I),I-1,F(I+M-1),I=2,M)
      J = NLOUT + 4
      WRITE (IPNT,130) (I,IIN1(I),I=1,J)
  130 FORMAT (10X,"IIN1(",I2,") =  ",I5)
  100 FORMAT (10X,"NUMBER OF OUTPUT LEVELS = ",F4.0//
     1        10X,"PDF TYPE =  ",I2//)
  120 FORMAT (10X,"X(",I3,") =",F11.4,25X,"CENT(",I3,") = ",F11.4)
  110 CONTINUE
      RETURN
      END
```

STATSSB

```
      SUBROUTINE STATSSB (IOFF,LIMIT,INC,NUMBER,II,HMIN,HMAX,IER)
     DIMENSION IN(256),IER(4097)
     DO 50 I=1,NUMBER
50   IER(I)=0
      BTM = -32767.
      TOP = 32767.
      IDV = 1
     ILM=IOFF+1+INC*LIMIT
     IDX=0
     IBK=0
     CALL RDBLK(II,0,IN,1,IE)
     IF(IE.NE.1)STOP INPUT FILE ERROR
     IS=IOFF+1
     AMAX=-1.E70
     AMIN=1.E70
     DO 1050 I=IS,ILM,INC
     IIT=(I-1)/256
     IF(IIT.NE.IBK)GOTO 1100
1101 IIP=I-IIT*256
     IDX=IDX+1
111  IF(IN(IIP)/IDV.GT.AMAX)AMAX=IN(IIP)/IDV
     IF(IN(IIP)/IDV.LT.AMIN)AMIN=IN(IIP)/IDV
     IF(IN(IIP)/IDV.LT.BTM)GOTO 1200
     IF(IN(IIP)/IDV.GE.TOP)GOTO 1300
     IBIN=(IN(IIP)/IDV-BTM)*FLOAT(NUMBER-2)/(TOP-BTM)+2
1050 IER(IBIN)=IER(IBIN)+1
 1051 ICNT = 0
      DO 10 J=1,NUMBER
   10 IF (IER(J).GT.0) GO TO 20
   20 JM2 = J - 2
      IF (JM2.LT.0) JM2 = 0
      MIN = 32767.*(JM2*2./NUMBER - 1)
      K = NUMBER
   30 IF (IER(K).GT.0) GO TO 40
      K = K - 1
      IF (K.NE.0) GO TO 30
   40 KP1 = K + 1
      MAX = 32767.*(KP1*2./NUMBER - 1)
      DO 60 L=1,NUMBER
   60 IF (IER(L).LT.0) ICNT = ICNT + 1
      IF (ICNT.GT.0) TYPE ICNT,"   NEGATIVE BIN COUNTS OCCURRED      "
     1,MIN,MAX
      TYPE "MIN = ",MIN,"     MAX = ",MAX
      IER(NUMBER+1) = 7
      HMIN = MIN
      HMAX = MAX
      RETURN
```

```
1100 CALL RDBLK(II,IIT,IN,1,IE)
     IF(IE.NE.1)GOTO 1051
     IBK=IIT
     GOTO 1101
1200 IBIN=1
     GOTO 1050
1300 IBIN=NUMBER
     GOTO 1050
     END
```

SUMMRYSB

```
C     SUBROUTINE SUMMRYSB
C     SUMMRY READS DATA FROM PROGRAMS IN THE OPTIMUM QUANTIZER
CALCULATION
C           ROUTINES AND PRINTS A DATA FILE CONTAINING A SUMMARY
C           OF THE QUANTIZER CHARACTERISTICS.  TO BE RUN WITH OPT1
C     AUTHOR:     CHAS GIMARC
C
C
C*****************************************************************
C
C
      SUBROUTINE SUMMRYSB (DEC,REC,NSPL,NBIN,NLOUT,NBLK,SDEV,RNVAR,
     1                    XMIN,XMAX,ITYP,CONVG,NIT,MSE,RITIM,SNR,IPNT)
      COMPILER FREE
      REAL DEC(257),REC(256),MSE
      NT = NLOUT + 1
      WRITE (IPNT,100) NSPL,NBIN,NLOUT,NBLK,SDEV,RNVAR
      WRITE (IPNT,110) XMIN,XMAX
      GO TO (20,21,22,23,24,25,26),ITYP
   20 WRITE (IPNT,120)
      GO TO 30
   21 WRITE (IPNT,121)
      GO TO 30
   22 WRITE (IPNT,122)
      GO TO 30
   23 WRITE (IPNT,123)
      GO TO 30
   24 WRITE (IPNT,124)
      GO TO 30
   25 WRITE (IPNT,125)
      GO TO 30
   26 WRITE (IPNT,126)
   30 WRITE (IPNT,130) CONVG,NIT,MSE,RITIM,SNR
      WRITE (IPNT,140) (J,DEC(J),J,REC(J),J=1,NLOUT)
      WRITE (IPNT,150) NT,DEC(NT)
  100 FORMAT(///5X,"OPTIMUM QUANTIZER CALCULATIONS"///5X,"QUANTIZER ",
     1       "PARAMETERS ARE:"//10X,"  OF SAMPLES FOR HISTOGRAM =",I7//
     2       10X,"  OF HISTOGRAM BINS",8X,"=",I7//10X,"  OF QUANTIZER",
     3       " LEVELS",6X,"=",I7//10X,"  OF BLOCKS TO QUANTIZE    =",
     4       I7//10X,"STANDARD DEVIATION          =",E14.4//10X,
     5       "NUMBER OF DEVIATIONS        =",F6.2)
  110 FORMAT(/10X,"MIN DECISION LEVEL",9X,"=",F10.3//10X,"MAX DECISIO"
     1       ,"N LEVEL",9X,"=",F10.3)
  120 FORMAT(/10X,"QUANTIZER TYPE",13X,"=  UNIFORM")
  121 FORMAT(/10X,"QUANTIZER TYPE",13X,"=  TRIANGULAR")
  122 FORMAT(/10X,"QUANTIZER TYPE",13X,"=  LAPLACIAN")
  123 FORMAT(/10X,"QUANTIZER TYPE",13X,"=  GAUSSIAN")
```

```
124 FORMAT(/10X,"QUANTIZER TYPE",13X,"=  GAMMA")
125 FORMAT(/10X,"QUANTIZER TYPE",13X,"=  OTHER")
126 FORMAT(/10X,"QUANTIZER TYPE",13X,"=  HISTOGRAM")
130 FORMAT(///5X,"CALCULATED RESULTS:",//10X,"CONVERGENCE LIMIT  =",
   1        E10.3//10X,"  OF ITERATIONS    =",I5//10X,"MEAN SQUARED ",
   2        "ERROR =",F9.7//10X,"CALCULATION TIME   =",F9.2,
   3        "  SECONDS"//10X,"SNR      =",F11.7///15X,"DECISION",
   4        " LEVEL",21X,"RECONSTRUCTION LEVEL"//)
140 FORMAT(13X,"D(",I3,") = ",F14.7,17X,"R(",I3,") = ",F14.7)
150 FORMAT(13X,"D(",I3,") = ",F14.7)
    RETURN
    END
```

THTSB

```
C      SUBROUTINE THTSB
C      CONSTRUCTS AN ARTIFICIAL INPUT HISTOGRAM FOR USE IN OTHER
C          PROGRAMS.  TESTHIST ALLOWS FOR HAND DATA ENTRY OR FOR
C          CALCULATION OF A HISTOGRAM BASED UPON EQUAL, TRIANGULAR,
C          LAPLACIAN, NORMAL, OR GAMMA AMPLITUDE DISTRIBUTIONS.
C          HISTOGRAM IS WRITTEN INTO AN INTEGER DATA FILE.  A PRINTED
C          OUTPUT IS OPTIONALLY AVAILABLE.  ALL HISTOGRAMS HAVE BEEN
C          NORMALIZED FOR MAXIMUM SENSITIVITY.
C      AUTHOR:  CHAS GIMARC
C      EXECUTION FORMAT:  CALL THTSB (NBIN,SDEV,ITYP,ICBIN)
C
C
C*****************************************************************
C
C
       SUBROUTINE THTSB (NBIN,SDEV,ITYP,ICBIN)
       INTEGER ICBIN(4097)
       DEL = 65536.
       SQR3 = SQRT(3.)
       SQR2 = SQRT(2.)
       FACT = 1.0E07
       C = 64000.*SQRT(SDEV)/(EXP(-2.*SQR3/SQRT(SDEV)))
       ICBIN(NBIN+1) = ITYP
       DO 210 I=1,NBIN
       POINT = DEL*(I - .5)/NBIN - 32768.
       GO TO (220,230,240,250,260),ITYP
C
C      FOR ALL PDF'S, ASSUME MEAN = 0
C
   220 ICBIN(I) = 1000
       GO TO 210
   230 IF (I.GT.NBIN/2) GO TO 232
       ICBIN(I) = IFIX(64000.*POINT/DEL + 32000.)
       GO TO 234
   232 ICBIN(I) = IFIX(-64000.*POINT/DEL + 32000.)
   234 GO TO 210
   240 POINT1 = DEL*I/NBIN - 32768.
       POINT2 = POINT1 - DEL/NBIN
       FACT1 = SQR2*ABS(POINT1)/SDEV
       FACT2 = SQR2*ABS(POINT2)/SDEV
       CBIN = FACT*(EXP(-FACT1)-EXP(-FACT2))/(POINT1-POINT2)
       IF (ABS(CBIN - IFIX(CBIN)).GE.0.5) CBIN = ABS(CBIN) + 1
       ICBIN(I) = IFIX(ABS(CBIN))
       GO TO 210
   250 ICBIN(I) = IFIX(EXP(-(POINT/SDEV)**2/2)*32000.)
       GO TO 210
   260 CBIN = C/SQRT(ABS(POINT)*SDEV)*EXP(-SQR3/2.*ABS(POINT)/SDEV)
```

```
      IBIN = IFIX(CBIN)
      IF (ABS(CBIN-IBIN).GE.0.5) IBIN = IBIN+1
      ICBIN(I) = IBIN
  210 CONTINUE
      RETURN
      END
```

ADPCOD

```
C
C
C     PROGRAM NAME:     ADPCOD
C     LANGUAGE:         FORT
C     DATE:              1/3/79
C     AUTHOR:           T.P.BARNWELL
C     CATEGORY:         SPEECH
C
C
C     SWITCH   TYPE   PURPOSE
C
C     P        L      PITCH FILE
C     I        L      INPUT FILE (SPEECH)
C     O        L      OUTPUT FILE (SPEECH)
C     C        L      FEEDBACK COEFFIENT FILE
C     X        L      QUANTIZED ERROR OUTPUT FILE
C     E        L      ERROR OUTPUT FILE
C     M        L      MULTIPLIER OUTPUT FILE
C     D        L      DATA FILE
C     L        L      LISTING FILE
C
C
C     PURPOSE
C     TO SIMULATE GENERAL AUDICRON SYSTEMS. SYSTEM IS CONFIGURED BY D
C     AND INPUT/OUTPUT FILES(EG. IF A /P FILE IS PRESENT,A PITCH S
C     ERROR CORRECTION IS DONE)
C
C
C             ------------------------------------
      COMPILER FREE
      REAL ICT
      DIMENSION OUTEMP(21)
      DIMENSION IQUN(512)
      DIMENSION AAA(64),ITIME(3),IDATE(3),AA1(64),BB(64),BB1(64)
      DIMENSION IINB(1536),IT(2),IOUTB(1280),IQERB(512),IERB(512)
      DIMENSION IMPYB(512),ABUF(128),AA(20),IPIT(256)
      COMMON /IBLK/ITEST(13),ICHAN(13),ILET(2,13)
      EQUIVALENCE (ITEST(1),IP),(ITEST(2),II),(ITEST(3),IOUT)
      EQUIVALENCE (ITEST(4),IA),(ITEST(5),IQ),(ITEST(6),IEE)
      EQUIVALENCE (ITEST(7),IM),(ITEST(8),IBOTH),(ITEST(9),ID)
      EQUIVALENCE (ITEST(10),IG),(ITEST(11),IB),(ITEST(12),IL)
      DATA ITEST/13*0/
      DATA ICHAN/1,2,3,4,14,6,7,2,8,9,13,-12,0/
      DATA ILET/1,0,200K,0,2,0,20000K,0,0,400K,4000K,0,10K,0,202K,0,
      110000K,0,1000K,0,40000K,0,20K,0,0,0/
      CALL ALL
      CALL    OPNALL(13,ITEST,ICHAN,ILET)
```

```
X     CALL OVERF(INST)
      IF(IBOTH.NE.0)II=IBOTH
      IF(IBOTH.NE.0)IOUT=IBOTH
      IF(II.EQ.0)STOP NO INPUT FILE
      ISS=1
      IBPX=0
      IERX=0
      IMX=0
      IS=1
      IFRAM=1
      IPX=2000
      IPPX=1
      IAX=2000
      IBX=0
      IBLK=0
      DO 62 I=1,20
62    OUTEMP(I)=0.
      DO 50 I=1,256
      IINB(I)=0
      IOUTB(I)=0
      IQUN(I)=0
      IQERB(I)=0
      IERB(I)=0
50    IMPYB(I)=0
      IQUAN1=0
      IQUAN2=0
      IMBK=0
      IERBK=0
      IF(ID.EQ.0)GOTO 1000
      READ(ID) NN,A,ICOEF,Q,ZK,ALIMIT,IFS
      IF(IA.EQ.0.AND.ICOEF.GT.0)READ(ID) (AA(I),I=1,ICOEF)
      IF(IA.NE.0)READ(ID)IFM
      IF(IP.NE.0)READ(ID) C,IPMAX
      READ(ID)ICT
200   NM=NN-1
      IF(IG.NE.0)READ(IG)(AAA(I),I=1,NM),(BB(I),I=1,NN)
      IF(IG.NE.0)GOTO 2001
      AAA(1)=-8000.*FLOAT(NN-2)/FLOAT(NN)
      BB(1)=-8000.*FLOAT(NN-1)/FLOAT(NN)
      DO 2050 I=1,NM
      AAA(I+1)=AAA(I)+16000./FLOAT(NN)
2050  BB(I+1)=BB(I)+16000./FLOAT(NN)
2001  SIG=0
      SNOIS=0
      CALL    RDBLK(II,IBLK,IINB(257),4,IE)
      IF(IE.NE.1)GOTO 9000
      CALL RDBLK(II,IBLK+4,IINB(1281),1,IE)
      ISET=IFS
      IF(IA.NE.0)CALL GETIN(IA,AA,ICOEF,ABUF,IAX,IBX,1,IE)
      IF(IA.NE.0.AND.IE.NE.1)GOTO 9000
      IF(IP.NE.0)CALL IGETIN(IP,IT,1,IPIT,IPX,IBPX,1,IE)
```

```
      IF(IP.NE.0.AND.IE.NE.1)GO TO 9000
C
C
C
1200 CONTINUE
      IF(ICT.GT.0)GO TO 999
      CALL    ERS(I)
      CALL FDELY(10)
      IF(ICT.LE.0)CALL IGRAF(150,620,3,IINB(IS+64),192,
      1"INPUT SPEECH",ISS)
      IF(ICT.LE.0)CALL IGRAF(150,200,3,IOUTB(IS+64),192,
      1"OUTPUT SPEECH",ISS)
      IF(ICT.LE.0)CALL IGRAF(150,410,3,IMPYB(IMX+64),192,
      1"QUANTIZER CONTROL",ISS)
      IF(ICT.LE.0)CALL IGRAF(620,580,4,IERB(IERX+128),128,"ERROR",IS)
      IF(ICT.LE.0)CALL IGRAF(620,200,4,IQERB(IERX+128),128,
      1"QUANTIZED ERROR",IS)
      IF(SIG.EQ.0.OR.SNOIS.EQ.0)GOTO 5467
      SN=10.*ALOG10(SIG/SNOIS)
      CALL TPLOT(0,0,0)
      CALL TPLOT(0,30,2)
      CALL PCR(31)
      TYPE "SIGNAL TO NOISE=",SN
5467 IF(ICT.LE.0)ACCEPT "TYPE 1 FOR CHANGE ",I
      IF(ICT.LE.0.AND.I.EQ.1)GOTO 500
555   IF(ICT.LE.0)ACCEPT "REPEAT COUNT=",ICT
999   ICT=ICT-1
      ISET=ISET+1
      IF(ISET.GT.IFS)GOTO 8111
8112 EST=0
      IF(ICOEF.EQ.0)GOTO 9011
      DO 90 I=1,ICOEF
      IF(ILET(1,13).EQ.0)EST=EST+AA(I)*OUTEMP(I)
90    IF(ILET(1,13).NE.0)EST=EST+AA(I)*IINB(256+IS-I)
9011 IF(IP.NE.0.AND.IT(1).NE.0)EST=EST+C*IQERB(IERX+256-IT(1))
X     CALL OVERF(INST)
X     IF(INST.NE.2)TYPE INST,ISS
X     IF(INST.NE.2)ICT=0
      SIG=SIG+FLOAT(IINB(256+IS))*FLOAT(IINB(256+IS))
      IF(ABS(EST).LT.1.E-10)EST=0
      DP=FLOAT(IINB(256+IS))-EST
      IERB(IERX+256)=DP/A
      QQ=QUAN(DP,A*Q,NN,IQUAN,AAA,BB)
      IF(IQUAN.GE.0)IQUAN=IQUAN+1
      IQUN(256+IERX)=IQUAN
      IQERB(256+IERX)=QQ/A
      SNOIS=SNOIS+(IINB(256+IS)-EST-QQ)*(IINB(256+IS)-EST-QQ)
      IF(EST+QQ.GT.77777K.OR.EST+QQ.LT.-77775K)TYPE "OUTPT OVR ON ",ISS
      IOUTB(256+IS)=(EST+QQ)
      IF(IP.EQ.0)GOTO 901
      IPPX=IPPX+1
```

```
      IF(IPPX.GT.IPMAX)CALL IGETIN(IP,IT,1,IPIT,IPX,IBPX,1,IE)
      IF(IPPX.GT.IPMAX)IPPX=1
901   IMPYB(IMX+256)=A*4000.
      IF(ICOEF.EQ.0)GOTO 40011
      DO 4001 I=1,ICOEF
4001  OUTEMP(ICOEF-I+2)=OUTEMP(ICOEF-I+1)
40011         OUTEMP(1)=EST+QQ
      IF(OUTEMP(1).GT.77777K)OUTEMP(1)=77777K
      IF(OUTEMP(1).LT.-77775K)OUTEMP(1)=-77777K
      IS=IS+1
      IF(IS.GT.1024)GOTO 5000
5001  IERX=IERX+1
      IF(IERX.GT.256)GOTO 6000
6001  IMX=IMX+1
      IF(IMX.GT.256)GO TO 7000
7001  ISS=ISS+1
      IF(IA.NE.0)IFRAM=IFRAM+1
      IF(IFRAM.GT.IFM.AND.IA.NE.0)GOTO 8000
8001  GOTO 1200
C
C
C
1000  ACCEPT "NO. OF QUANTIZER LEVELS=",NN
      ACCEPT "INITIAL QUANTIZER LEVEL( DELTA(0))=",A
      ACCEPT "NO. OF PREDICTOR COEFS=",ICOEF
      ACCEPT "QUANTIZER GAIN FACTOR(Q)=",Q
      ACCEPT "QUANTIZER MINIMUM(MIN)=",ZK
      ACCEPT "QUANTIZER LIMIT=",ALIMIT
      ACCEPT "FRAME SIZE=",IFS
      IF(IA.NE.0)GOTO 1001
      IF(ICOEF.EQ.0)GOTO 1001
      DO 1002 I=1,ICOEF
      TYPE "TYPE ",I," COEF"
1002  ACCEPT AA(I)
1001  IF(IA.NE.0)ACCEPT "FRAME LENGTH=",IFM
      IF(IP.NE.0)ACCEPT "PITCH SYN FEEDBACK=",C
      IF(IP.NE.0)ACCEPT "PITCH FRAME=",IPMAX
      ACCEPT "REPEAT COUNT =",ICT
      GOTO 200
C
C
C
5000  DO 5050 I=1,256
      IINB(I)=IINB(1024+I)
5050  IOUTB(I)=IOUTB(I+1024)
      IS=1
      IF(IOUT.NE.0)CALL WRBLK(IOUT,IBLK,IOUTB(257),4,IE)
      IF(IE.NE.1)GOTO 9000
      IBLK=IBLK+4
      CALL RDBLK(II,IBLK,IINB(257),4,IE)
      IF(IE.NE.1)GOTO 9000
```

```
      CALL RDBLK(II,IBLK+4,IINB(1281),1,IE)
      GOTO 5001
6000  IERX=1
      DO 6050 I=1,256
      IERB(I)=IERB(I+256)
      IQUN(I)=IQUN(I+256)
6050  IQERB(I)=IQERB(I+256)
      IF(IB.NE.0)CALL WRBLK(IB,IERBK,IQUN,1,IE)
      IF(IB.NE.0.AND.IE.NE.1)GOTO 9000
      IF(IEE.NE.0)CALL WRBLK(IEE,IERBK,IERB,1,IE)
      IF(IEE.NE.0.AND.IE.NE.1)GOTO 9000
      IF(IQ.NE.0)CALL WRBLK(IQ,IERBK,IQERB,1,IE)
      IF(IQ.NE.0.AND.IE.NE.1)GOTO 9000
      IERBK=IERBK+1
      GOTO 6001
7000  DO 7050 I=1,256
7050  IMPYB(I)=IMPYB(I+256)
      IF(IM.NE.0)CALL WRBLK(IM,IMBK,IMPYB,1,IE)
      IF(IM.NE.0.AND.IE.NE.1)GOTO 9000
      IMBK=IMBK+1
      IMX=1
      GOTO 7001
9000  SN=10.*ALOG10(SIG/SNOIS)
      IF(IL.EQ.0)CALL FBACK
      WRITE(IL)SN,NN,ICOEF,Q,IFS
      CALL FBACK
500   TYPE "NUMBER OF LEVELS=",NN
      ACCEPT "NUMBER OF LEVELS=",NN
      NM=NN-1
      AAA(1)=-FLOAT(NN-2)/2.
      BB(1)=-FLOAT(NN-1)/2.
      DO 20501 I=1,NM
      AAA(I+1)=AAA(I)+1.
20501        BB(I+1)=BB(I)+1.
      TYPE "CURRENT QUANTIZER GAIN FACTOR(Q)=",Q
      ACCEPT "Q=",Q
      TYPE "CURRENT QUANTIZER MINIMUM(MIN)=",ZK
      ACCEPT "MIN=",ZK
      TYPE "CURRENT END VALUE CONTROL(MAX)=",ALIMIT
      ACCEPT "MAX =",ALIMIT
      IF(IP.NE.0)TYPE "CURRENT C=",C
      IF(IP.NE.0)ACCEPT "NEW C=",C
      ACCEPT "TYPE 1 FOR COEF CHANGE ",I
      IF(I.NE.1)GOTO 555
      ACCEPT "NUMBER OF COEFS=",ICOEF
      IF(ICOEF.EQ.0)GOTO 555
      DO 550 I=1,ICOEF
      TYPE "COEF NO. ",I
550   ACCEPT "=",AA(I)
      GOTO 555
8000  IFRAM=1
```

```
      CALL    GETIN(IA,AA,ICOEF,ABUF,IAX,IBX,1,IE)
      IF(IE.NE.1)GOTO 9000
      GOTO 8001
 8111 SQAC=0.
      DO 1287 I=1,IFS
      ES=0.
      IF(ICOEF.EQ.0)GOTO 1287
      IF(IA.NE.0)GOTO 1287
      DO 1289 JJK=1,ICOEF
 1289 ES=ES+AA(JJK)*IINB(256+IS+I-JJK)
 1287 SQAC=SQAC+(FLOAT(IINB(256+IS+I))-ES)**2
      A=SQRT(SQAC/IFS)/4000.
      IF(A.GT.ALIMIT)A=ALIMIT
      IF(A.LT.ZK)A=ZK
      ISET=1
      GOTO 8112
      END
```

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